Abstract—This paper proposes an online path planning and motion generation algorithm for heterogeneous robot teams performing target search in a real-world environment. Path selection for each robot is optimized using an information-theoretic formulation and is computed sequentially for each agent. First, we generate candidate trajectories sampled from both global waypoints derived from vertical cell decomposition and local frontier points. From this set, we choose the path with maximum information gain. We demonstrate that the hierarchical sequential decision-making structure provided by the algorithm is scalable to multiple agents in a simulation setup. We also validate our framework in a real-world apartment setting using a two-robot team comprised of the Unitree A1 quadruped and the Toyota HSR mobile manipulator searching for a person. The agents leverage an efficient leader-follower communication structure where only critical information is shared.

I. INTRODUCTION

There has been tremendous attention for search behaviors using single and multiple agent systems. These studies can be classified into various categories, such as offline [15, 11, 1, 22] and online [26, 27, 17, 16, 14] coverage path planning, exploration and mapping [2, 9, 7, 8, 18, 19, 20, 12], and search itself [31, 25, 13, 21, 4, 3, 32]. With improvements to robot mobility, sensing and computing power there have been many successful applications [16, 24, 28, 29, 5, 10] in real-world settings like moon exploration, search and rescue, and unmanned surveillance with teams of robots made up of UAVs, legged systems and mobile robots. Several of these groups have ongoing work focusing on using multiple agents to improve the performance of their system.

This study attempts to solve the problem of target search with a single robot or multiple robots within a given search boundary in real-time fashion. The contribution of this paper is an online search algorithm which can be scaled to n heterogeneous agents for performing a probabilistically optimal search in real-world environments. Because the target search problem can be formulated in varying ways, we first discuss a set of assumptions for which we are solving. Such conditions are prior knowledge of the search region, the presence of a target prediction model, and characteristics of the target (i.e., the target being static or dynamic). Our online planning algorithm accounts for changes to the environment and uses sensor observations to perform a probabilistically optimal continuous search of the region.

II. METHODS

A. Problem Definition

We define a cooperative multi-agent target search problem with a hierarchical knowledge structure. This problem aims to find a control policy (sensing action) for multi-agent system (MAS) search in a known area for a target with known probability distribution in the predefined search region. Each agent’s control policy is supposed to find control inputs that maximize target information (or reduce target uncertainty). Assuming a heterogeneous robots setup, we denote the index of the agent in each equation.

B. Target Estimation

We use Bayesian Inference to recursively estimate target state, x, through sequential observations, y. Bayesian inference is a commonly used framework used to estimate a target.
state in a probabilistic manner. This inference model aims to predict the posterior distribution of target position at time $k$, namely, $p(x_k)$. Bayesian filtering includes a prediction step and a correction step using incoming sensing information. Assuming that the prior distribution $p(x_{k-1})$ is available at time $k-1$, the prediction step attempts to estimate $P(x_k | y_{1:k-1}^n)$ — where $n$ is the number of agents — from previous observations as follows.

$$p(x_k | y_{1:k-1}^n) = \int p(x_k | x_{k-1}) p(x_{k-1} | y_{1:k-1}^n) dx_{k-1},$$

where $p(x_k | x_{k-1})$ is the target’s motion model based on a first order Markov process. Then, when the measurement $y_k^n$ is available, the estimated state can be updated as

$$p(x_k | y_k^n) = \frac{p(y_k^n | x_k) p(x_k | y_{1:k-1}^n)}{p(y_k^n | y_{1:k-1}^n)}$$

where $p(y_k^n | y_{1:k-1}^n) = \int p(y_k^n | x_k) p(x_k | y_{1:k-1}^n) dx_k$ and $p(y_k^n | x_k)$ is a sensing model for multi agent system, which can also be decomposed to each agent’s sensing model $p(y_k^n | x_k)$. For the correction stage, the measurement of all agents are used to modify the prior estimate, leading to the target belief. If a static target is assumed the target motion model can be described as $p(x_k | x_{k-1}) = N(x_{k-1}; x_k, \Sigma)$, only containing a noise term with the previous target state. Instead if a dynamic target is assumed to have some constant velocity, we can represent the target model as $p(x_k | x_{k-1}) = N(x_{k-1}; x_k + V \Delta, \Sigma)$.

$$C. \text{ Hierarchical Bayesian Model}$$

We propose a leader-follow hierarchy setting in which we assume that the first agent is the leader and the second is the sub-leader, consisting of sequentially lower-class followers. Assuming that decisions (desired paths) can be mapped into the expected sensing outputs, within the proposed hierarchy structure, our decision-making process can be generalized to $n$-multi agent systems, estimating target state $x_l$ with expected observations of all agents, $[y_{1:t+1}^l, y_{2:t+1}^l, \cdots, y_{n:t+1}^l]$ with time horizon $h$. To be more specific, given the target state probability $p(x)$ and the expected sensing outputs $\hat{y}$ from the agents, the belief state variable $\hat{x}_i^l = p(x | \hat{y})$ can be written as

$$\hat{x}_1^l = p(x | y_{1:t+1}^l) \quad s_1^l = \gamma(\hat{x}_1^l)$$
$$\hat{x}_2^l = p(x | y_{1:t+1}^l, y_{2:t+1}^l) \quad s_2^l = \gamma(\hat{x}_2^l)$$
$$\cdot \quad \cdot \quad \cdot$$
$$\hat{x}_n^l = p(x | y_{1:t+1}^l, \cdots, y_{n:t+1}^l) \quad s_n^l = \gamma(\hat{x}_n^l)$$

where $\hat{y}$ denotes the set of expected outputs up to the $i$-th agent. In this way, the expected belief state can be updated sequentially based on the decisions of each agent, and can be used as known information for the $i + 1$ agent. Here, $\gamma(\ast)$ is a decision making function given a target belief state whose output is desired path for each agent.

$$D. \text{ Information-Theoretic Objective Path planning}$$

Our strategy is to maximize the information gain regarding the target belief state in a greedy fashion. Given each robot’s expected information gains and travel costs, we obtain paths for all agents that maximize the overall utility.

$$\max_{x_{1:n}} \mathbb{E}[U(x_1, y_2, \cdots, y_n)]$$

where $\mathbb{E}[U]$ refer to the expected value of the utility function given the target belief and the sensing outputs. This utility function can be calculated based on the path candidates for each agent in order to select the best path (or sequence of control inputs). Given a target belief at time $t$, obtaining the desired path for each agent allows MAS to gather information as quickly as possible. Our method aims to find the optimal path using a sampling-based optimization problem over a time horizon with an information-theoretic utility function. The utility function is described as

$$\mathbb{E}[U(x_t, y_{1:t+1}, y_{2:t+1}, \cdots, y_{n:t+1})] = \sum_{i=1}^{n} (IG(s_i) - c(s_i))$$

$$1) \text{ Path Selection:}$$ To obtain the best path for each agent, we use a sampling-based optimization approach. The proposed strategy is to create global and local candidate paths. The goal points of paths can be sampled from waypoints within a search map boundary, sampled based on the entropy map $M$, which considers the target estimation model being updated by local measurements. Precisely, the global candidate points are sampled from a vertical cell decomposition of sub-regions whose occupancy grid type is unknown, $M_{[m=0.5]}$. Cells with the value 0.5 are unknown while cells that are occupied or unoccupied are given 1.0 and 0.0, respectively. Local goal points are sampled from the cluster of frontiers [30], which is defined as the boundary between known (occupied or free).
and unknown areas, which are potentially informative. The frontiers can be obtained from the current entropy map.

\[ p(x) = \text{uniform over } M_{[m=0.5]} \]  

(6)

Given the next viewpoint candidates and the current robot position, we use an A* planner to generate an obstacle-free path, \( s \), for each agent. We note that any other planner like RRT or PRM could be used in its place. The set of paths to each global target point and a local target point are of different lengths and therefore must be re-parameterized. The reason for this re-parameterization is that the optimization problem should consider path length based on the robot’s speed and the time horizon. In order to consider the difference in the speed of robots, the interval between the sampling points along the generated path is set accordingly. For example, if the path length \( |s| \) is 10 and \( ds = 2 \), we can sample five points along the trajectory. In order to avoid overlap between the computed FOV area, we sparsely sample points along a path to calculate the expected amount of information. Based on the number of sampled points along a path, we compute the Information Gain, denoted \( IG(s) \), by the following equation:

\[
IG(s) \approx \sum_{i=1}^{N_s} H(FOV(s^i)) \\
= \sum_{i=1}^{N_s} \left[ \sum_{j=1}^{N_e} \left( p(m_{i,j}) \log(p(m_{i,j})) + (1 - p(m_{i,j})) \log(1 - p(m_{i,j})) \right) \right]
\]

(7)

where \( s^i \) denotes the \( i \)-th sampled point and \( p(m) \) is the occupancy probability, while \( N_s \) and \( N_e \) are the number of sampling points and the number of cells in the FOV given the sampled points, respectively. Thus, The \( IG(s) \) is calculated by summing over the FOV regions defined by sampled points through the trajectory. When calculating the information gain, the paths of the robots do not overlap as much as possible by not calculating the information gain corresponding to the path selected from the agent in the upper hierarchy. The proposed search algorithm is described in the Algorithm 1.

III. Results

A. Simulation Results

In this section we present python-based simulation results of our proposed approach for a multi-agent search behavior and demonstrate the scalability of the algorithm. It is assumed that the simulation environment (search region) and all the static obstacles have a rectangular shape and obstacles are not known in advance. Each agent is equipped with a simulated ray sensor, which has a square field of view with limited range, \( F(x,y) \), determined by the 2D position of the agent. Given the resolution of the map, the entire environment can be decomposed into square-type grid cells. To achieve robust

\[ Fig. 2. \] Simulation results using increasing number of agents. (a) 2 agents in a 13x13 grid. (b) 3 agents in a 13x13 grid. (c) 5 agents searching a 25x25 grid space. (d) 10 agents searching a 35x35 grid space.

\[ Fig. 3. \] Simulation results with different conditions. (a) One time search (static target) (b) Continuous search (dynamic target).

\[ Fig. 4. \] Average search time with varying number of agents.
collision avoidance, we use a dynamic window approach to generate the control input to navigate towards goal points.

1) Single Search vs Continuous Search: In order to test the search performance, simulations were conducted under various initial conditions. Depending on how the search map is updated (time-varying condition), we can implement one time search (similar to the exploration and mapping problem) and a continuous search. As shown in Fig 3, in the case of three agents, we can prove that the agents were able to effectively search for the target over the search region.

2) n-Agent Case: To validate the scalability of the proposed method, we test the exploration with n agents. As the number of agents increases, we enlarge the search space. Fig. 2 demonstrates the trajectories of each agent in the case number of agents equals to 2, 3, 5, and 10. Each color represents the trajectory of a different agent. These results demonstrate that our algorithm is scalable and can be extended to a general multi-agent system and still perform in real-time.

3) Search Time: The search time varies depending on the initial condition or the dimension of the search space. Therefore, for accurate comparison, given a fixed size of the search map (13x13), fixed maximum moving speed (1m/s), the search time was compared. Fig. 4 shows the average search time (the entropy reduction rate) for three cases. By adding an additional agent, the time to completion is reduced by more than half.

B. Experimental Results

We used the Unitree A1 quadraped and the Toyota HSR mobile manipulation robot for experimentation of multiple agent target search. The A1 is equipped with a Velodyne VLP-16 3D Lidar and a RealSense D435 camera. On-board computing is performed in an Intel NUC Mini PC, which communicates with the low-level control systems. The HSR is equipped with a Hokuyo 2D Lidar, a RGB-D camera, and an on-board Jetson TK1 GPU. We assume that both robots have perfect localization, although in practice we provide it via Episodic non-Markov Localization [6]. The use of such different systems demonstrates that our algorithm is well suited to perform with a heterogeneous team, each with varying motion models.

Experiments were performed in the Anna Hiss Gymnasium apartment at the University of Texas. Fig. 5 shows two different moments in the search. The search map is 20(m) x 10(m) and the maximum velocity of each agent are 0.3(m/s) and 1.0(m/s) for the HSR and A1, respectively. In the top left of Fig. 5 (a) and (b) is the global entropy map. Regions in yellow indicate that they have been explored (known to be free or occupied), while regions in white have high uncertainty. In the lower-left of each figure (a) and (b), the target is found in the hallway along the left side of the apartment setup. The red and black markers indicate the next waypoints for each agent, which is determined by using the search server. In (b), the object detection feed is shown as the two agents approach the target of interest. Finally, Fig. 6 shows resulting trajectories for the two agents for one of experimental trials. The video demo can be found at https://youtu.be/7WMqG7EiUVY.
This paper addresses online search for a heterogeneous multi-agent system. We employ an information-theoretic utility function and sampling-based optimization to obtain each agent’s path. A hierarchical decision-making structure allows us to reduce computational burden and perform the search in real-time. Simulation results show that our proposed algorithm proves its scalability and that it can be extended to the general case of multiple agents. We further validate this algorithm by implementing it in a real-world environment. Overall results validate the effectiveness and robustness of the proposed method.

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