Distributed Multi-Target Search and Tracking Using a Coordinated Team of Ground and Aerial Robots

EXTENDED ABSTRACT

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Abstract— **The authors recently developed a distributed version of the PHD filter (for multi-target tracking) and combined this with Lloyd's algorithm to enable a team of homogeneous robots to search for and track an unknown and time-varying number of dynamic targets. In this paper we extend this previous work to allow a heterogeneous team of ground and aerial robots to perform the search and tracking tasks in a coordinated manner. Both types of robots are equipped with sensors that have a finite field of view and which may receive both false positive and false negative detections. The ground robots have greater computational power while the aerial robots have greater mobility and may vary their elevation, with an accompanying trade off between the size of the sensor field of view (FoV) and the accuracy and reliability of the sensor. We develop two new distributed algorithms to provide filter updates and to make control decisions in this heterogeneous team. Both algorithms only require robots to communicate with nearby robots and use minimal bandwidth. We demonstrate the efficacy of our approach through a series of simulated experiments which show that the heterogeneous teams are able to achieve more accurate tracking in less time than our previous work.**

I. INTRODUCTION

Target search and tracking are fundamental problems in robotics, with applications to mapping, environmental monitoring, surveillance, search and rescue, and more [1]. Many situations call for performing these two tasks simultaneously, where the same team of robots must search a space in order to detect the presence of any targets of interest and then track the motion of any detected targets. Most approaches utilize a homogeneous team of robots, including our prior work using ground-only [2] and air-only [3] teams. This simplifies the solution by allowing all robots to utilize the same governing equations. However, we will demonstrate that a heterogeneous team is able to achieve superior results, as long as the coordination mechanism allows the different types of robots to take advantage of their unique capabilities.

The coordination of mixed air-ground robot teams has been studied in recent years [4]–[8]. However, in all of these prior works a ground station was used to monitor the air team, to facilitate communication between air and ground robots, or to make control decisions. The main contribution in our work is the development of a distributed algorithm that enables a mixed air and ground robot team to coordinate to search for and track multiple targets.

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In our previous work we developed the distributed probability hypothesis density (PHD) to perform multi-target tracking using a large team of robots [2], [3]. The robots use the output of the PHD filter as the importance weighting function within Lloyd's algorithm [9]. This effectively drives the robots to follow previously detected targets and to explore unknown areas that may contain targets. In this paper we will demonstrate that a straightforward application of our previous approach to a heterogeneous team is not as effective as an approach that treats each type of robot differently. We propose a distributed algorithm that utilizes the superior mobility of aerial robots and the superior computational power of ground robots to distribute tasks among subteams within the full team in order to achieve more accurate tracking in less time compared to a homogeneous team of either ground or aerial robots.

II. PROBLEM FORMULATION

A team of ground and aerial robots track the motion of an unknown number of targets, which move in a convex polygonal environment. The environment must be convex in order to compute the Voronoi cells, though this requirement can be relaxed [10], [11]. At each time step, a robot (either ground or air) collects a set of measurements, the size of which varies over time due to false positive and false negative detections and due to the motion of both targets and robots, which cause targets to enter and leave the sensor field of view (FoV). The team seeks to determine the set of targets in the environment using a modified version of our previous distributed PHD filter [3].

A. Distributed PHD Update

Due to their superior computational resources, we utilize the ground subteam, along with its associated Voronoi partition, to maintain the distributed PHD filter. This requires three rounds of communication. First, each aerial robot sends its pose and measurement set to each ground robot whose Voronoi cell overlaps with its sensor FoV. Each ground robot then computes the integral of the measurement likelihood over the intersection of the aerial robot FoV and its Voronoi cell and sends this back to the aerial robots. Each aerial robot then computes the full integral and sends this back to the ground robots, which perform the PHD updates.

B. Distributed Goal Assignment

All robots use Lloyd's algorithm, with the PHD as the importance weighting function, to select exploration goals

[9], [12]. Since aerial robots do not store any PHD information on board, they must communicate with ground robots to compute their exploration goals. This requires two rounds of communication. First, each aerial robot sends its Voronoi cell boundary to all ground robots with overlapping Voronoi cells. Second, each ground robot computes the partial integral over the intersection of the Voronoi cells and sends this back to the aerial robot. The aerial robot is then able to compute the full integral and, thus, its goal.

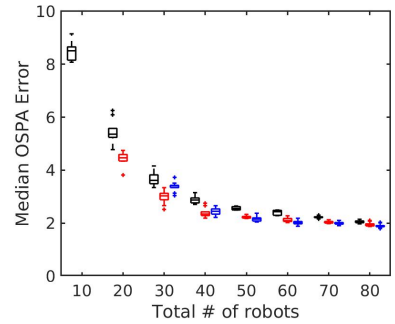
III. SIMULATIONS

We conduct a set of simulated experiments using MATLAB to demonstrate the efficacy of our proposed distributed estimation and control algorithms. All robots know their pose at all times and are modeled as point robots that are both holonomic and kinematic. Each robot is equipped with an isotropic sensor with a finite sensing range. As an aerial robot moves up in elevation, its sensor FoV increases in size while the detection probability decreases and the noise and clutter increase. All of the sensor and target models match those from our previous work [3]. The environment is an open 100×100 m area with no obstacles. The PHD is represented by a uniform grid of particles. The grid resolution is 1 m, and initially the weight of each particle is set to 10^{-4}, so that the total expected number of targets is initially 1.

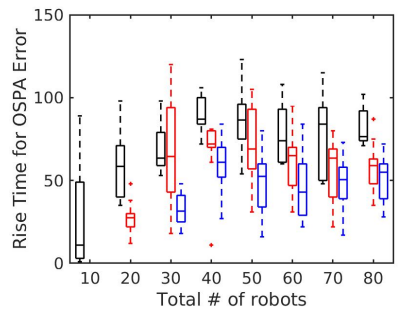
To extract an estimated target set, we measure the error between this estimated target set and the true target set using the Optimal SubPattern Assignment (OSPA) metric [13], which is commonly used in the PHD filter literature.

1) Comparison with Previous Method: We consider robot teams consisting of 20 aerial robots plus a varying number of ground robots, from 10–70, for a total team size of 30–90 robots. In the first scenario (`old`), we use a naïve extension of our previous work [3]: the team uses a single Voronoi diagram and both types of robots maintain portions of the PHD. In the second scenario (`new`), the heterogeneous team will use the algorithm proposed in this paper. The results show that teams using `new` have a lower steady-state OSPA error and the spread in values is smaller compared to teams using `old` and that teams using `new` have a lower 95% rise time of the OSPA error metric and a smaller spread.

2) Moving Targets: To further explore the effects of coordination, we conduct trials using three different team compositions: ground robots with 0, 10, or 20 aerial robots. In each case there are initially 10 moving targets, though the number changes over time as targets enter and leave the environment. As expected, all three team compositions show decreasing OSPA errors and rise times as the total number of robots increases, as Fig. 1 shows. This is due to the ability of the team to better cover the boundaries of the environment to ensure that fewer new targets are missed while simultaneously tracking previously detected targets. As the team size increases, we see that the gap between the three team compositions narrows, the results become more consistent, and there are diminishing returns for adding more robots. In every case, the ground-only team performed worse than either of the teams with aerial robots, demonstrating the utility of coordination. The team with 20 aerial robots has a significantly lower and more consistent rise time than the team with 10 aerial robots for the same case, supporting the intuition that the aerial robots provide more consistent information (at a lower quality) than the ground robots.



(a) OSPA – 10 Dynamic Targets



(b) Rise Time – 10 Dynamic Targets

Fig. 1. Boxplots showing the results of teams of 10–80 total robots, including 0 (black), 10 (red), and 20 (blue) aerial robots, tracking 10 dynamic targets. (a) shows the OSPA error while (b) shows the 95% rise time of the OSPA error.

3) Team Composition: To further explore the effects of team composition that we observed before, we consider the scenario of 51 robots tracking 20 dynamic targets. Note that the team always has at least one ground robot, to maintain the PHD filter, and one aerial robot. The minimum error occurs when the number of ground and aerial robots are nearly equal. In this case, the two types of robots can essentially pair off, with the aerial robot providing lower-quality coverage of a larger area. This reduces the number of targets that ground robots lose track of due to repeated false negative detections over a short time span. This is especially helpful since the targets have the same maximum speed as the ground robots.

IV. CONCLUSIONS

In this paper we propose a distributed method that enables a heterogeneous team of ground and aerial robots to effectively search for and track an unknown number of targets in a known environment. The coordination mechanism takes advantage of the relative strength of each type of platform: ground robots offer increased computational ability and more precise sensors while aerial robots offer increased mobility and a variable sensor field of view. We demonstrate the effectiveness of the proposed heterogeneous coordination mechanism through a series of simulated experiments.

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