Heterogeneous multi-robot systems Cooperative Exploration of Unknown Environment

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Abstract. This paper introduces a novel method for the coordinated control of heterogeneous multi-robot systems composed of a UGV and a UAV and focuses on cooperative exploration in unknown environments. The proposed approach utilizes a numerical optimization solver to manage the non-linear dynamics and constraints of both agents. We introduce a weighting parameter to adapt the team behavior either prioritizing proximity between the agents or independently pursuing the exploration. The proposed solution has been extensively tested in a simulation environment and the experimental results demonstrate the method's computational efficiency, adaptability, and suitability for real-time deployment in autonomous exploration missions. This approach advances multi-robot coordination by providing a flexible and robust framework for heterogeneous agent collaboration in complex, unstructured environments.

Keywords: cooperative trajectory planning, multi-robot system, autonomous vehicle, 3D Dubins model, potential field method.

1 Introduction

In recent years, progress in robotics and Artificial Intelligence (AI) has enabled the development of autonomous robotic systems capable of performing increasingly complex tasks, spreading the application scenarios from industrial settings [1] to extreme and potentially hazardous environments [2]. The use of multi-robot systems has gained significant interest due to the potential benefit offered by the synergistic and coordinated operation between multiple robotic units. Heterogeneous multi-robot systems, such as those combining UAVs and UGVs, in particular, leverage complementary agents' capabilities as rapid aerial sky-view form the UAV and detailed data at ground level from the UGV.

In coordinated exploration scenarios, continuous information sharing between robots allows for dynamic planning, maximizing the team's effectiveness in data acquisition and environmental coverage. A constant connection between agents improves mapping accuracy and resource optimization [3]. However, in contexts where communication is limited or intermittent, this becomes critical. More advanced solutions, such as those proposed by [4, 5], involve partial mapping of the environment or limited UAV support to avoid critical communication dependencies.

This work presents an algorithm for cooperative exploration of an unknown environment by a heterogeneous multi-robot team composed of a UGV and a UAV. The proposed system is based on the optimal trajectory planning of one agent to minimize the distance from the trajectory of the teammate.

2 Proposed Method

The proposed method has been inspired by the 2024 Leonardo Drone Contest challenge where we are engaged to design and develop a heterogeneous multi-robot system to autonomously navigate an unknown environment looking for targets. In such a framework we have to coordinate two robotic platforms, i.e. a UGV which is capable of accurately localising within the environment exploiting a 2D LiDAR sensor and NAV2 navigation software stack, and a UAV which navigates the environment fusing the VIO estimation provided by the Intel Realsense T265 camera with the PX4 EKF running on the flight control unit. The agents' primary goal is to explore the unknown environment as soon as possible performing SLAM to create a shared map and hence localize given targets within such a map. The agents can share information like their own position on the global map, the position of the identified targets and the planned trajectory being executed.

Within the proposed solution, the UGV computes its own exploration trajectories by exploiting a frontier-based exploration algorithm with the goal of expanding a shared map of the environment. Then it shares the planned trajectory to the UAV. Conversely, the UAV selects the target position by exploiting a frontier-based exploration algorithm as well, and then computes its trajectory optimizing a cost function which weights, among other things, the UGV's trajectory with the aim of maintaining a trajectory that stays as close as possible to the teammate over time. This spatial proximity improves cooperative localization techniques as they navigate the environment and, in real-life operations, could improve communication reliability and data sharing.

UAV target points selection. The UAV operates within a 3D volumetric map composed of voxels, where each voxel represents free, occupied or unknown space. To efficiently explore the environment, we use frontier-based exploration methods from the literature [6] ables to identify and choose target positions that lead to the exploration of new areas.

Obstacle Modelling. The UAV has sensors capable of providing discrete 3D samples of obstacle surfaces, such as a stereo camera or LiDAR. The purpose of these sensor measurements is twofold since they are both used to construct a volumetric map of the environment and to introduce the knowledge of obstacles in the trajectory planner. To efficiently store and process this volumetric map, we employ a k-d tree data structure [7].

Using the KD-tree representation, we compute a potential field $P(\mathbf{p})$ that assigns to each point $\mathbf{p} \in \mathbb{R}^3$ a potential value based on its distance to the closest obstacle. More in detail, for any point $\mathbf{p}$ in the 3D space, we first compute its distance to the closest occupied voxel as:

$$d(\mathbf{p}) = \min_{\mathbf{o}\in\mathcal{O}} \|\mathbf{p} - \mathbf{o}\|, \tag{1}$$

where $\mathcal{O}$ denotes the set of occupied voxels (obstacles) in the map, and $\|\cdot\|$ represents the Euclidean distance. Then, the potential field is defined as:

$$P(\mathbf{p}) = \frac{\alpha}{d(\mathbf{p}) - d_0}, \tag{2}$$

where α is a positive scaling factor and d_0 is a safety distance threshold. The potential field increases as the point approaches an obstacle, effectively creating a repulsive effect that pushes the UAV from getting too close to obstacles.

The advantage of such an approach lies in functioning entirely within the discrete domain of the voxel map, eliminating any assumptions about obstacle shapes or explicit geometric modeling.

Vehicle Models. The dynamics of the agents have been modeled by exploiting the unicycle model for the UGV vehicle, and the 3D Dubin model for the UAV.

The unicycle model is a simple yet effective representation of the kinematics of a ground vehicle moving in a plane. With such a model, the vehicle is characterized by its position $(x_{\text{ugv}}, y_{\text{ugv}}) \in \mathbb{R}^2$ and orientation $\theta_{\text{ugv}} \in [-\pi, \pi)$, whereas the control inputs are the linear velocity v_{ugv} and angular velocity ω_{ugv}:

$$\begin{cases} \dot{x}_{\text{ugv}} = v_{\text{ugv}} \cos\theta_{\text{ugv}}, \\ \dot{y}_{\text{ugv}} = v_{\text{ugv}} \sin\theta_{\text{ugv}}, \\ \dot{\theta}_{\text{ugv}} = \omega_{\text{ugv}}, \end{cases} \tag{3}$$

where $\dot{x}_{\text{ugv}}$, $\dot{y}_{\text{ugv}}$, and $\dot{\theta}_{\text{ugv}}$ denote the time derivatives of the position and orientation.

Although multicopters are capable of hovering and moving omnidirectionally, we adopt the 3D Dubins model to constrain motion to smoother trajectories, as proposed by [8]. This approach is particularly beneficial for tasks that require stable imaging or precise sensor data acquisition, as it reduces the impact of sudden directional changes on the quality of the collected data.
The state of the UAV is defined by its position $(x_{\text{uav}}, y_{\text{uav}}, z_{\text{uav}}) \in \mathbb{R}^3$ and orientation described by the yaw angle $\psi_{\text{uav}} \in [-\pi, \pi)$ and pitch angle $\theta_{\text{uav}} \in \left[-\frac{\pi}{2}, \frac{\pi}{2}\right]$. The vehicle moves forward at a constant speed $v_{\text{uav}} > 0$. The control inputs are the yaw rate ω_ψ and the pitch rate ω_θ:

$$\begin{cases} \dot{x}_{\text{uav}} = v_{\text{uav}} \cos\theta_{\text{uav}} \cos\psi_{\text{uav}}, \\ \dot{y}_{\text{uav}} = v_{\text{uav}} \cos\theta_{\text{uav}} \sin\psi_{\text{uav}}, \\ \dot{z}_{\text{uav}} = v_{\text{uav}} \sin\theta_{\text{uav}}, \\ \dot{\theta}_{\text{uav}} = \omega_\theta, \\ \dot{\psi}_{\text{uav}} = \omega_\psi. \end{cases} \tag{4}$$

Optimal trajectory computation. Given the known trajectory of the UGV, denoted as $\mathbf{p}_{\text{ugv}}(t)$, we formulate an optimal control problem to compute the control inputs for the UAV. The objective is to find the control inputs that generate a trajectory for the UAV, satisfying the dynamics of the 3D Dubins model, starting from the current position and ending at the selected target position, while minimizing a cost function.

Let $\mathbf{x}_{\text{uav}}(t)$ be the state vector of the UAV at time t, and $\mathbf{u}_{\text{uav}}(t) = [\omega_\theta(t), \omega_\psi(t)]^T$ be the control inputs, with admissible set $\mathcal{U}$. The free-time optimal control problem is defined as:

$$\min_{\mathbf{u}_{\text{uav}}(t),\,T} \quad J = w_T T + w_d \int_0^T \|\mathbf{p}_{\text{proj}}(t) - \mathbf{p}_{\text{ugv}}(t)\|^2 \, dt + w_p \int_0^T P(\mathbf{p}_{\text{uav}}(t)) dt, \tag{5}$$

$$\text{subject to} \quad \dot{\mathbf{x}}_{\text{uav}}(t) = f\big(\mathbf{x}_{\text{uav}}(t),\, \mathbf{u}_{\text{uav}}(t)\big), \tag{6}$$

$$\mathbf{x}_{\text{uav}}(0) = \mathbf{x}_{\text{uav},0}, \tag{7}$$

$$\mathbf{x}_{\text{uav}}(T) = \mathbf{x}_{\text{goal}}, \tag{8}$$

$$\mathbf{u}_{\text{uav}}(t) \in \mathcal{U}, \tag{9}$$

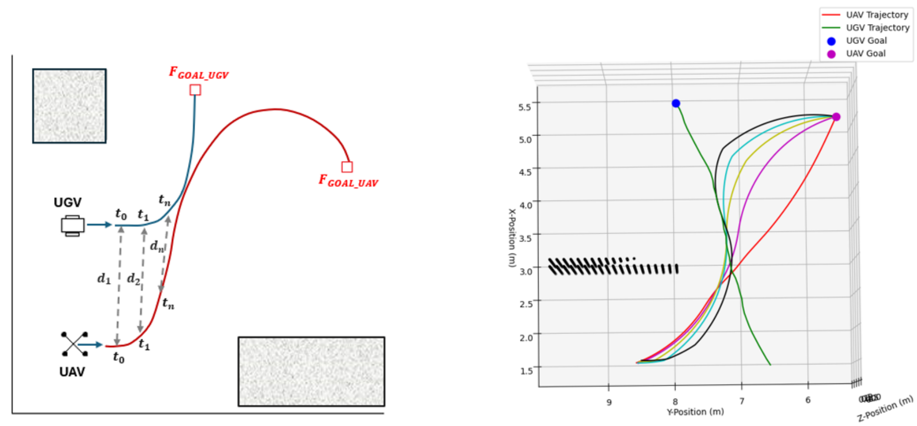
where w_T, w_d, and w_p are scalar weights for the traversal time, relative distance, and potential field terms, respectively, used to balance their relative importance in the optimization; T is the total traversal time of the trajectory; the term $\mathbf{p}_{\text{proj}}(t) = [x_{\text{uav}}(t), y_{\text{uav}}(t)]^\top$ represents the projection of the UAV's position onto the ground plane. Equation (6) represents the dynamics of the UAV as defined by the 3D Dubins model as in Equation (4).

Note that we have omitted explicit collision avoidance constraints on the UAV's state being within the free space. Instead, obstacle avoidance is implicitly handled by the potential field term in the cost function (third term in Equation (5)), which penalizes proximity to obstacles.

The solution to this optimal control problem is a trajectory for the UAV that efficiently guides it from the current position to the target position in minimal time. It maintains close proximity to the UGV's trajectory projected onto the ground plane (second term in Equation (5)), as evinced in Figure 1a, enhancing communication reliability and localization accuracy.

3 Results

To prove the effectiveness of the proposed cooperative trajectory planning method, we designed a synthetic environment in the ROS/Gazebo framework that replicates the typical indoor layout of the Leonardo Drone Contest challenge [9]. Within such an environment we set one UGV and one UAV in a known starting position to explore the given volume. The UGV explores the environment by means of the frontier-based exploration algorithm. Conversely, the UAV selects the target positions by means of the frontier-based exploration algorithm but then the trajectory is computed as previously discussed. To evaluate the impact of the proximity weight w_d in the cost function (Equation (5)).



(a) (b)

Fig. 1: (a) Schematic of the UAV trajectory respect to the UGV. (b) Planned UAV trajectories for varying w_d values; the UGV's trajectory is shown in green, while the black points are samples of the obstacle wall.

We present the results obtained for a single step in the exploration process, which involves reaching a target waypoint or goal point (i.e. the selected frontier point) for both agents. Figure 1b illustrates the planned UAV trajectories for different values of w_d. The UGV and UAV goal points are represented by the blue and red dots respectively. The UGV's trajectory is shown in green for reference. The black curve represents the UAV trajectory with the highest w_d value used in the simulations, indicating a strong influence to stay close to the UGV. The UAV closely follows the UGV's path on the ground plane, maintaining minimal distance over time. The red curve corresponds to $w_d = 0$, meaning the UAV plans its trajectory without considering the UGV's trajectory, focusing solely on reaching the goal position efficiently while avoiding obstacles via the potential field. Intermediate curves represent decreasing values of w_d, showing a gradual shift from closely following the UGV to prioritizing the UAV's own objectives.

Throughout all simulations, the UAV successfully avoids obstacles by effectively utilizing the potential field in the cost function. This approach demonstrates the advantage of incorporating the potential field directly into the cost function, as it simplifies the optimization problem by removing the need for obstacle modelling.

The ability to adjust w_d provides flexibility in mission planning, enabling the UAV to balance its objectives between staying close to the UGV and pursuing its own goals. A higher w_d is beneficial in scenarios where maintaining close communication links and cooperative localization are critical. Lower values of w_d allow more autonomy to the UAV which could be advantageous in time-sensitive exploration tasks.

4 Conclusions

We presented a method for coordinated control of heterogeneous multi-robot systems, enabling each agent to perform cooperative or independent exploration. The problem was solved using a numerical optimization solver capable of handling non-linear dynamics and constraints. Adjusting the weight w_d, the UAV can effectively balance its objectives between staying close to the UGV and optimizing its own path to the goal position. The potential field integrated into the cost function ensures obstacle avoidance without increasing the complexity of the optimization process. The method demonstrates computational efficiency and flexibility, making it suitable for real-time applications in cooperative autonomous vehicle missions.

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