Cooperative Flight in Complex Environments using Heterogeneous UAVs and LiDAR-based Relative Localization

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***Abstract*— Existing research has achieved impressive results in giving the Unmanned Aerial Vehicles (UAVs) the ability to operate in challenging conditions thanks to the fusion of multiple sensory modalities and utilizing multiple UAVs, but many parts of the environment remain unreachable for current UAV approaches. Designing a cooperating UAV team capable of flying through constrained passages while simultaneously achieving accurate localization requires developing new methods for cooperative localization, navigation, multi-UAV path planning, and coordination. Our approach to multi-UAV cooperative flight utilizes relative localization using direct UAV detections from a 3D Light Detection and Ranging (LiDAR) and hierarchical team structure. A larger primary UAV (pUAV), equipped with 3D LiDAR, can quickly and accurately map large areas while having accurate localization robust to decreased visibility conditions. A miniature secondary UAV (sUAV), equipped with cameras, can fit into tight passages and explore spaces unreachable for larger UAVs. Combining UAVs of different sizes and sensory equipment effectively increases the operational space of the UAV team while increasing its robustness to challenging conditions. In this paper, we describe the methods enabling our approach, namely the LiDAR-based relative localization and relative pose estimation, cooperative UAV guiding, and multi-UAV exploration. The described approaches have been successfully deployed in multiple real-world experiments with all the algorithms running on board the UAVs with no external localization system nor external computational resources.**

MULTIMEDIA ATTACHMENT

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I. INTRODUCTION

Unmanned Aerial Vehicles (UAVs) have gained an invaluable role in inspection and mapping tasks due to their ability to quickly reach spaces with difficult accessibility. However, the UAVs' ability to fly to such spaces is always limited by their physical size and their sensory capabilities. The design of such UAVs requires careful consideration and making compromises between the UAVs' size and sensory payload. 3D Light Detection and Ranging (LiDAR) sensors exhibit significant accuracy and robustness to challenging environmental conditions but are generally heavy and power-consuming. 3D LiDAR-equipped UAVs need to be relatively large, which limits their ability to fly through tight spaces. Camera-equipped UAVs can be comparatively smaller and lighter and thus fly through many narrow gaps. However, camera-based navigation generally exhibits lower accuracy due to the need to estimate the distance of features in the environment and heavily depends on the texture of the environment and on the visibility conditions.

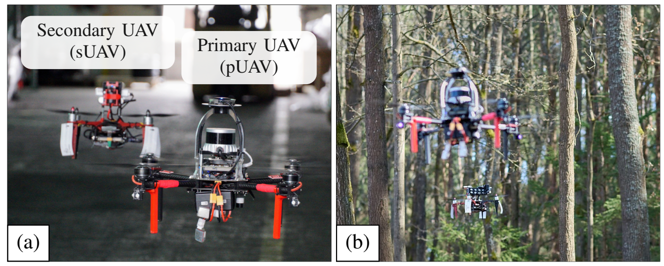

Fig. 1: The LiDAR-equipped primary UAV and the camera-equipped secondary UAV operating in (a) an industrial warehouse and (b) a cluttered forest environment.

We combine both of these sensory modalities in a single heterogeneous UAV team, focusing on the case of a large primary UAV (pUAV) and small secondary UAV (sUAV) (see Fig. 1). The pUAV is equipped with 3D LiDAR, utilized for localization, mapping, and detection of the cooperating UAV. The pUAV acts as a leader of the team. The sUAV follows commands of the pUAV and can reach places inaccessible to the pUAV. The UAVs communicate over a wireless network. We assume that the UAVs operate in Global Navigation Satellite System (GNSS)-denied environment and no external localization system is available. All the algorithms are designed to run on board the UAV hardware with no ground station nor external computational resources available.

In this paper, we describe our approaches to relative localization between the UAVs, cooperative guiding of the sUAV by the pUAV, and cooperative mapping and exploration using the multi-UAV team.

A. Related work

Existing multi-UAV approaches mostly focus on teams of homogeneous UAVs of the same size and sensory equipment. In the recent DARPA Subterranean challenge, although many teams employed heterogeneous teams of ground robots and UAVs, the UAVs deployed in the exploration missions were usually equal in size and sensory payload with all teams predominantly relying on LiDAR-based localization [1]–[6]. UAV swarming approaches, which demonstrate great benefits in comparison to single UAV approaches, usually focus on the use of homogeneous UAVs [7], [8], which restricts them to the properties of their specific type of sensory payload. Similarly, state-of-the-art UAV exploration approach RACER [9] performs space decomposition to make

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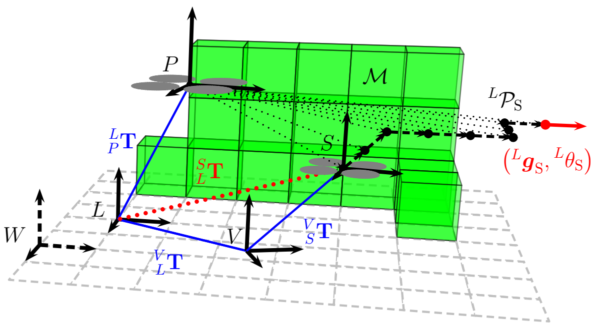

Fig. 2: The pUAV with body frame P is localized in its local frame L, builds dense occupancy map $\mathcal{M}$, and plans collision-free paths for both UAVs. The sUAV with body frame S is localized in its local frame V. W denotes the fixed world frame. All the reference frames are gravity-aligned. The pUAV periodically guides the sUAV to follow the planned path ${}^{L}\mathcal{P}_{\mathrm{S}}$. Black dotted lines mark the line of sight between the pUAV position and the sUAV waypoints.

the UAVs explore distinct regions but does not distinguish between their possibly different physical sizes and thus different capabilities. Employing heterogeneous teams of UAVs in such tasks requires new approaches, which take into account the different capabilities of the specific UAVs, such as their physical sizes and sensory equipment.

Approaches for the use of heterogeneous UAV teams combining LiDAR- and camera-equipped UAVs in inspection tasks were recently proposed in [10], [11] and evaluated in simulations. An approach for cooperative mapping using a team of heterogeneous nano UAVs was proposed in [12]. A method for collaborative localization in a heterogeneous UAV swarm was proposed in [13]. However, deploying such methods in real-world applications still requires novel approaches to path planning, multi-robot coordination, and relative localization.

In GNSS-denied environments, accurate relative localization is crucial for effective cooperation. The different sensory modalities present in heterogeneous robot teams, along with the constrained computational hardware available on board the UAVs, pose a significant challenge. Our relative localization solution is based on direct detections of a cooperating UAV from a 3D LiDAR sensor, as the 3D LiDAR can directly provide accurate 3D position of the UAV without requiring any additional hardware. A similar approach was employed in [7], where the authors utilized 3D LiDAR detections to provide decentralized odometry for a LiDAR-equipped UAV swarm.

In the heterogeneous UAV team, we want to guide the less-capable UAVs by more-capable UAVs, thus compensating for the worse sensory equipment but keeping the desired abilities to, e.g., pass through narrow gaps. Therefore, we have designed a cooperative guidance approach, where the larger UAV with 3D LiDAR is guiding the smaller UAV equipped only with cameras.

The closest multi-UAV cooperation methods [14]–[17] to our cooperative guiding approach used a leader-follower scheme with one UAV moving through the environment and the other UAVs tracking the leader. However, these works all dealt with UAVs that are equal in size. Novel approaches are needed in mixed-size UAV team scenarios requiring a miniature UAV with limited or absent obstacle-sensing capability to pass through a narrow gap untraversable for the leader. In such scenarios, which match inspection and data-gathering tasks in hard-to-reach areas, the obstacle avoidance and visibility-maintaining constraints conflict as the leading UAV cannot directly lead a secondary UAV through narrow openings. Thus, the leader must guide the UAV from a distance using communication and precise relative localization.

II. Localization and Relative Pose Estimation

We utilize direct detections of the sUAV obtained from pointcloud produced by the 3D LiDAR of the pUAV. The detection can be either marker-less or utilizing reflective markers. The marker-less UAV detection approach is described in [18] in detail. Essentially, an occupancy map of the environment is constructed, and the UAV is detected as a flying object not connected to the background.

However, marker-less detection may be too computationally demanding, especially if we want to run additional software on board the pUAV, such as a global mapping and exploration pipeline. Therefore, we designed a reflective marker-based detection approach. The sUAV is equipped with reflective tapes on its legs (see Fig. 1). Highly reflective points in the environment are detected based on the thresholding of the reflectivity values of the LiDAR points, and UAVs are detected as flying clusters surrounding these highly reflective points.

The detections provide highly accurate 3D positions of the sUAV. To enable effective collaboration between the UAVs, the relative orientation of the sUAV is also necessary. The relative orientation is obtained by fusion of the detections with the local odometry of the sUAV, as described in [19] in detail. The UAVs communicate over a wireless network and the sUAV transmits its Visual-Inertial Odometry (VIO) output to the pUAV. The reference frames present in the fusion problem are depicted in Fig. 2. The relative pose estimation module on board the pUAV solves the problem of estimating the transformation

$$ {}^{V}_{L}\mathbf{T} = \begin{bmatrix} {}^{V}_{L}\mathbf{R}(\theta) & {}^{V}_{L}\boldsymbol{t} \\ \mathbf{0}^{\mathrm{T}} & 1 \end{bmatrix} \in SE(3) \tag{1} $$

between the local VIO reference frame V and LiDAR Simultaneous Localization and Mapping (SLAM) reference frame L. The transformation is estimated from a set of LiDAR-VIO pose correspondences in a sliding window by solving a Non-linear Least Squares (NLS) problem formulated as

$$ {}^{V}_{L}\hat{\boldsymbol{t}}, \hat{\theta} = \arg\min_{{}^{V}_{L}\boldsymbol{t}, \theta} \frac{1}{2} \sum_{i} \rho \left(\left|\left| {}^{V}_{L}\mathbf{R}(\theta) {}^{L}\boldsymbol{d}_{[t_i]} + {}^{V}_{L}\boldsymbol{t} - {}^{V}\boldsymbol{p}_{[t_i]} \right|\right|^2 \right), \tag{2} $$

$$ {}^{V}_{L}\boldsymbol{t} \in \mathbb{R}^3, \;\; \theta \in [-\pi, \pi], \tag{3} $$

where ${}^{V}_{L}\boldsymbol{t}$ is the relative translation vector between the reference frames, θ is the relative heading, ${}^{L}\boldsymbol{d}_{[t_i]}$ is the LiDAR

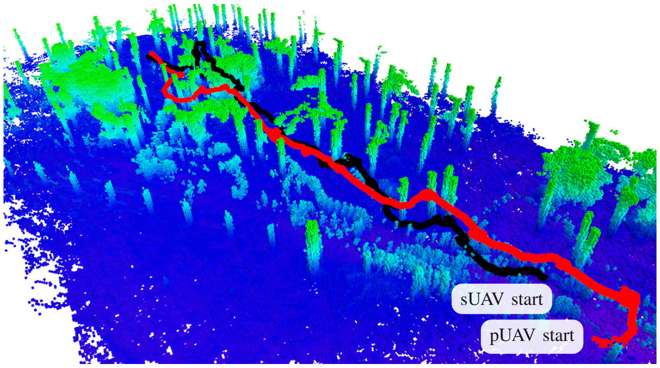

Fig. 3: Occupancy map from the cooperative forest flight and the UAV trajectories (pUAV - red, sUAV - black). For clarity, the map was sliced at the maximum height of $4\,\mathrm{m}$ above the ground.

detection position at time t_i, and ${}^{V}\boldsymbol{p}_{[t_i]}$ is the corresponding VIO position. $\rho()$ denotes the loss function used for reducing the influence of outliers on the optimization solution. The obtained solution, along with the LiDAR detections and VIO odometry output is then passed to a Kalman filter-based estimator, that estimates the state vector

$$\boldsymbol{x}^{\mathrm{KF}} = \begin{bmatrix} {}^{L}\boldsymbol{x}^{\mathrm{T}} & {}^{L}\boldsymbol{v}^{\mathrm{T}} & {}^{L}\phi & {}^{L}\omega \end{bmatrix}^{\mathrm{T}}, \quad (4)$$

where ${}^{L}\boldsymbol{x}$ is the 3D position of the sUAV in the LiDAR SLAM frame, ${}^{L}\boldsymbol{v}$ is the velocity, ${}^{L}\phi$ is the heading, and ${}^{L}\omega$ is the heading rate. The Kalman filter-based estimator compensates for possible delay caused by processing the LiDAR data and compensates for possible lag of the NLS solution, as the formulated NLS problem assumes constant relative transformation over the course of the sliding window.

III. Cooperative guiding

To compensate for possible drift of the sUAV's VIO and provide the sUAV with the obstacle avoidance capabilities of the pUAV, we have designed a cooperative guiding approach, which utilizes the estimated relative pose. Preliminary experiments on guiding based on raw LiDAR detections are described in [20] and the method for cooperatively guiding the sUAV between obstacles while maintaining visibility is described in [21].

The pUAV performs high-level planning for both itself and the sUAV on its accurate occupancy map constructed from the LiDAR data. The planned path for the sUAV is periodically transformed to the reference frame of the sUAV based on the estimated relative pose between the UAVs and transmitted to the sUAV. Furthermore, a guiding viewpoint is selected for the pUAV, such that the line-of-sight (LOS) visibility between the UAVs is maintained during the guiding process. The guiding viewpoint is obtained by constructing a set of 2D polygons representing regions with LOS visibility of the sUAV's path, safe space that is sufficiently distant from obstacles, and space that is too close to the sUAV's path. By combining these polygons, a guiding viewpoint is selected.

Fig. 3 shows the UAV trajectories and occupancy map

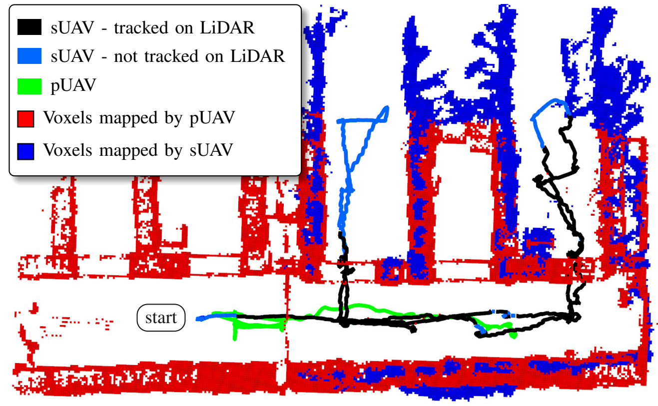

Fig. 4: Global occupancy map projection along with the UAV trajectories traversed in a cooperative mapping experiment in a real-world industrial warehouse.

Fig. 5: Cooperative multi-UAV mapping and exploration in an industrial warehouse.

from a real-world flight, where the pUAV guided the sUAV to fly through a forest based on the occupancy map constructed from the LiDAR data. The sUAV did not perform any mapping and only utilized its camera for VIO. All obstacle avoidance maneuvers of the sUAV were performed based on the commands from the pUAV.

IV. Cooperative mapping and exploration

The described approach was deployed in cooperative mapping and exploration scenarios in an industrial warehouse. The pUAV was equipped with the Ouster OS0-128 3D LiDAR for localization and mapping, while the sUAV carried the RealSense T265 tracking camera for VIO and Realsense D435 depth camera for occupancy mapping. Both UAVs performed local occupancy mapping, and the local maps were merged on board the pUAV during the flight. Fig. 4 shows the global map obtained in an experiment, where the pUAV was being sent to waypoints in a main corridor of the warehouse, while the sUAV autonomously explored adjacent side corridors. Fig. 5 shows a photo from the experiment.

Building on top of this mapping approach, we have designed a frontier-based exploration method for the UAV team, taking into account the different sizes and sensory capabilities of the UAVs, described in [22] in detail. The approach finds points of interest in the environment as frontiers on the global occupancy map. Accessibility of the points of interest is quickly evaluated using the SphereMap algorithm [23]. The accessible points of interest are allocated to the individual UAVs by solving a minimum-cost flow problem. Finally, collision-free paths for both UAVs are planned on board the pUAV and subsequently followed by the UAVs, while the distance between the UAVs is periodically monitored to prevent collisions.

V. Discussion and future work

Heterogeneous UAV teams exhibit great robustness and suitability for operation in complex environments thanks to their adaptability to various environmental conditions. LiDAR-based relative localization can provide accurate 3D positions between the UAVs and thus enable tight cooperation in complex tasks. We have focused on a team consisting of a large LiDAR-equipped pUAV and a small camera-equipped sUAV and designed an approach enabling such a team to cooperatively explore and map complex GNSS-denied environments with all algorithms running on board the UAVs. Our work has highlighted several areas worth further research. To provide more accurate and reliable localization for the UAV team, we want to explore methods of uncertainty-aware cooperative localization, i.e., how to effectively compare the uncertainty of the different localization methods running on board the different UAVs in order to provide a consistent localization estimate for the individual UAVs and enable operation in areas of various sensory degradations. To improve the reliability of such a system in exploration tasks, methods of uncertainty-aware exploration shall be developed, i.e., deciding when the localization of the individual UAVs is reliable enough for them to operate individually and planning rendezvous when the localization uncertainty gets too large for reliable operation. Finally, efficient path planning methods for deadlock-free operation of mixed-size UAV teams in cluttered environments should be explored.

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