Development of a heterogeneous aerial swarm control framework for forest management

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Abstract

As the prevalence of UAVs is increasing, they are becoming more accessible for wider applications. Our interest is in application of UAVs for forest management challenges including monitoring health and safety and commercial exploitation in a sustainable manner. We propose a swarm control framework for managing a group of UAVs for aforementioned tasks, including survey of tree health with infrared cameras and chemical sensors, detecting potential risky situations of illegal logging, smoke and fires, and estimating potential volume measurements. The proposed framework manages planning flight trajectories, sensor fusion and collaborative mapping. On the next stage, we plan to simulate the framework in ROS/Gazebo environment, and further to implement a pilot project with a group of DJI Phantom quadrotors and a large-size fixed-wing UAV.

Keywords: robotics, algorithms, swarm control, robotic framework, unmanned aerial vehicle (UAV)

1. Introduction

Over the last decade unmanned aerial vehicles (UAVs) becoming increasingly used all over the world to collect data for various applications including urban search and rescue[1] and forest monitoring[2], as a result of miniaturization and cost reduction of GPS receivers, inertial navigation system, computers, motors, batteries and sensors for remote sensing.

UAVs are competing with aircrafts and satellites, bringing the advantages, such as low material and operational costs and flexibility in different sensors loadout, i.e. choosing sensors according to the mission objectives[3]. Moreover, data acquired with UAVs usually have higher spatial resolution, which is essential for assess local-scale variation in forest stand and species measures[2]. Disadvantages are limited flight time (current systems typically have limited operation maximum of 1-2 hours) and payload capacity, limiting simultaneous acquisition of the entire area of interest.

In the literature, rotary-wing and fixed-wing UAVs are both equally distributed among various case studies. In the vast majority, off-the-shelf solutions are preferred over self-designed and self-constructed UAVs. Different types of sensors are used in experiments: visible-red, green, and blue, multispectral invisible and near-infrared, middle-infrared, thermal infrared imagery, and LRF[4]. Forest applications span over different types of missions, including available resources estimation, species classification, spread of diseases mapping, fire and its effects monitoring, spatial gaps quantification etc.

As UAVs applications continue to spread across different domains, there is increasing need for control framework that incorporates forestry specific mission planning, sensor fusion and control framework. Using heterogeneous aerial robotic swarm that could successfully combine long endurance, range, and processing capabilities of mothership vehicle with low cost, flexibility and maneuverability of UAVs swarms was shown to be applicable for cooperative search, acquisition, and tracking missions in urban environment[5]. Therefore we recognize significant potential advantages of such architecture in forestry applications, which could reduce mission time and increase operational coverage.

The rest of this position paper is organized as follows. We review common missions that influenced our framework composition in Section 2. Section 3 outlines applicable hardware architecture and in Section 4 we focus on framework's individual components, e.g. assignment and tracking task status for individual UAVs.

2. Typical UAV-assisted forest management missions

Information about vegetation conditions of a forest is important both for monitoring protected areas and for estimating potential economic value of the forest. Sensors being used in majority of case studies are near-infrared spectrometers and hyperspectral cameras[6,7].

Estimation of dendrometric parameters missions involve acquiring imagery from UAVs in order to estimate Lorey's mean height, dominant height, stem number, basal area, and stem volume estimation of stands using various statistical models. This mission type is used to estimate available resources, identify potential areas of logging, and provide information on plant growth dynamics and biomass allocation. In addition, it makes possible to identify and quantify spatial gaps in forests that could indicate illegal logging activities.

Species classification goal is to differentiate forest species and provide species distribution maps. Knowledge of such distributions is an important information, as it plays important role in sustainable forest management, as some tree species provide higher market value timber, influencing both economic value and potential illegal logging. This information also allows identification of invasion species, allowing earlier interventions.

Post-fire recovery monitoring involves analyzing burned areas and capturing ongoing processes of post-fire recovery: agamic regeneration, deadwood dynamics, and logging activities with or without log extraction[8].

Forest fire measuring during an ongoing forest fire UAVs could measure location and shape of the fire front, its rate of spread, and the fire flame height using visual and infrared cameras[4] and provide information that is necessary to predict fire spread direction and help plan firefighting processes.

Forest health monitoring goal is to produce distribution maps of dead trees and infestation levels to support intervention by authorities.

3. Heterogeneous swarm structure

We investigate robot swarm that is composed of one main vehicle (mothership) and multiple simple UAVs (drones) being connected through wireless network. The motherships act as data storage, recharging and sensor fusion stations, assist negotiation between agents, and supervise a mission while drone control is achieved using cooperative mapping. Each set of drones is assigned to a particular mothership. In the role of the mothership an aircraft, a ship or a ground vehicle could be used.

Drones are small light UAVs used for the data collection and equipped with communication devices to coordinate their operations locally. Commercial off-the-shelf UAVs are usually not intended for group operation, and thus require hardware upgrades. We also assume that an individual UAV is equipped with a low-level control system that provides stability and altitude-hold capability. The choice of deployed sensory loadout on UAVs depends on specific mission planned and on required spatial and temporal scales of the analysis.

The framework is designed in a way that each drone could operate autonomously and recognize other neighboring drones within the limited operational area in order to form cooperative groups.

4. Framework structure

One common task for all above mentioned forestry missions is mapping. Using collective sensory data, it is possible to overcome the individual drone limitations and address the issue with environmental conditions variability. SAGE experiment addresses this issue, demonstrating the usage of a small UAVs group to collectively monitor an agricultural field with weed mapping[10,11]. Network composition is based upon heterogeneous aerial robot network architecture for search and tracking developed by Elston and Frew[12].

Figure 1 depicts a schematic representation of a heterogeneous swarm control architecture. The highest level is mothership-drone coordination level that is used to allocate specific tasks through negotiation between

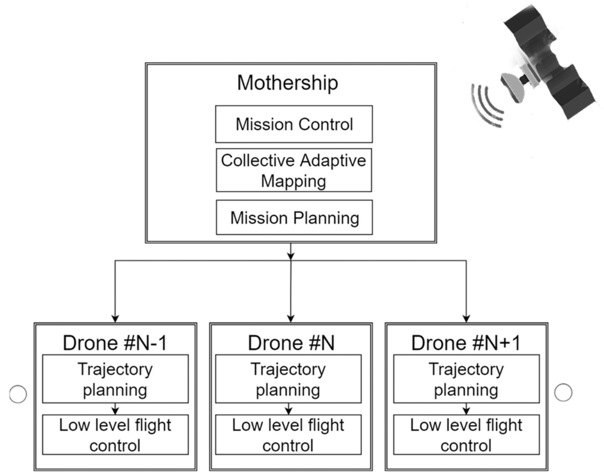

Figure 1. Framework structure

mothership and individual drones. When the mission type and parameters are specified mothership is issuing subtasks that are derived from the planning layer on the mothership vehicle to the trajectory generation layer on each drone. Here, each task is converted into a trajectory, which is passed to the lowest Flight Control Layer that performs low-level drone control. This decomposition is minimizing the computations performed by drones. The mothership has a GPS-receiver and can plan its activities on the global scale, including cooperation with other motherships of a large fleet.

While payload capabilities of UAVs fundamentally limit amount of sensory information, communication, and processing that can be acquired and carried out, a size of the mothership vehicles allows them to carry much complex systems that can perform communications over larger distances, store and process more information than individual drones. Consequently, swarm architecture utilizes technical advantages of a mothership to minimize the amount of communication, planning, and coordination performed by drones.

4.1. *Mission control*

A mothership keeps tracking drones health (flight hours, battery status, etc.). When amount of data acquired by a drone is reaching drone memory capacity limit, the drone returns to the mothership to perform fast data transfer for storage and processing. Drone is landed on the mothership using methods of autonomous landing with infrared beacons, e.g.[13,14]. Localization during landing could be assisted using a variation of the method by Yakovlev et.al.[15]. The same landing procedure is triggered by a low level of drone battery charge.

We also use data preprocessing that keeps tracking drone's data quality rating. As each data chunk contains drone signature, if during data preprocessing we identifying problem data (e.g., corrupted data or contradictory data about a same particular map cell that comes from two different drones) we consequently mark a map cell as unexplored and add it to a task list with lowering drone data quality rating.

4.2. *Mission planning*

Mapping is achieved using task assignment based on a decomposed coverage map. The map is decomposed into cells, which are defined by its boundary coordinates and data acquisition parameters (e.g., velocity, flying altitude etc.). The division of the mission area into cells simplifies motion planning of each agent, and it insures that no two agents inspect the same cell at the same time.

Mothership uses a network to assign drones with responsibilities for free cells by transmitting cell information. We treat drones that inspect cells as a simple collision-free model in C-space while agents are treated as points simplifying collision prevention strategy.

Covering mission area effectively with our drones involves two stages - area decomposition into cells and path planning inside the cells. Our framework is being developed with modularity in mind so it supports different methods of decomposition and path planning in individual cells.

4.3. *Collective Adaptive Mapping*

Some of mission objectives require a precise mapping only for particular affected areas, so a uniform coverage of the environment becomes ineffective. Therefore we add adaptive strategies to increase efficiency of a swarm by allocating more drones to such areas, while other areas could be only monitored superficially or even entirely skipped. At first mission, the exploration area is divided into multiple cells and each cell is coarsely inspected with a fast flyby by a drone, with interesting areas being added to the map and communicated to the mothership and other drones. The mothership issues special orders to inspect all interesting areas with more precision by splitting interesting area into smaller cells. Drones that are not performing high precision data acquisition could be assigned to search the rest of the environment in order to mark new potentially interesting areas.

5. Conclusions

The designed framework of coordinated control for a mothership and drones in heterogeneous swarm architecture fully utilizes individual advantages of each robot type improving mission performance. This is a position paper that overviews our framework, while implementation of modules is an ongoing work. Our goal in developing this framework is to demonstrate applicability of aerial swarm robotics approach to forestry using heterogeneous robots, as forestry missions are complex problems with large economic impact. We intend to implement aforementioned missions in ROS Gazebo simulator[16] and use the simulated experiments results to evaluate economic advantages and drawbacks of a heterogeneous swarm robotics approach within the forestry industry.

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