Coverage Control of Collaborating Drones using Spherical Cameras

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***Abstract*—This research proposal addresses the area coverage problem using a swarm of collaborative drones. Each drone will be equipped with a spherical camera that will provide information about its neighboring drones. Rather than relying on a wireless exchange of the geolocation coordinates between each drone, computer vision algorithms will be employed to provide relative localization between the swarm's members. Based on this information, each drone will compute its 3D-Voronoi responsibility cell and adjust its position so as to cover as much area as possible. Experimental studies will take place in the Robotics lab to validate the efficiency of the suggested control laws. This research will take place at NYUAD's robotics and Kinesis Motion Capture CTP and will supplement the existing research efforts between NYUAD's international partners in US, Europe and Asia.**

I. Background and Rationale for Research

The usage of UAVs (Unmanned Air Vehicles) such as drones has become increasingly commonplace due their ability to accomplish basic tasks in fields ranging from transport to surveillance [1]. Yet, to tackle complex assignments such as Search and Rescue (SaR) missions requires more intricate UAVs or the utilization of multiple distributed smaller drones in collaboration [2]. While the latter option is cost-effective, reliable and scalable there are also critical design challenges associated with creating efficient multi-UAV systems. The most immediate issue being the construction of an ad-hoc communication network structure and multi-agent coverage control that allows for timely collaboration between the distributed drones. For example, in SaR the UAVs are typically flown in fixed formations relative to one another due to the difficulty in establishing areas of responsibility and maintaining communication. However, an enhanced system would allow the drones to self-organize using decentralized, adaptive control law and thus optimize sensing configurations and strategies. In addition, current traditional multi-UAV platforms are often centralized, meaning, it involves a base control station for facilitating communication. While such network architecture is precise the maintaining of links to the control station puts heavy constraints on battery power and bandwidth. Thus, a mesh network structure offers a more optimal approach.

Work involving small drones also has limitations in terms of processing, memory storage, energy consumption and network availability. As such the communication range for smaller UAVs is typically restricted. There are theoretical methods for improving the operational range by making use of multi-hop communication chains between UAVs [3] and positioning using communication relays [4]. However, most of these theoretical postulations rely on common assumptions such as accurate channel models and symmetric links, known workloads, static locations or simplistic movement models [5]. In practice, such conditions are difficult to replicate. Thus, the extensive research conducted in the field of mobile ad hoc networks (MANETS) does not address the fluid topology of UAV networks involving vanishing and changing nodes often coupled with unstable links. In the case of larger UAV systems or swarms, the problem of interference becomes common as information is broadcast from a number of sources at frequent intervals [5].

Accordingly, these communication challenges also directly hinder UAV localization. It is not feasible to constantly update the entire swarm of each UAV's position coordinates. Furthermore, there is already inherent uncertainty associated with most positioning systems such as GPS, meaning that the combined system elicits considerable error. As a result, a more robust method is needed to identify the position of the UAVs.

II. Previous Work

This research will be conducted in collaboration with Professor Tzes and the NYUAD Robotics lab. It will act to supplement his extensive work on the topic of visual area coverage. Some of his recent projects involve the development of complex algorithms for partitioning the region of responsibility [6] as well as accounting for the unique considerations needed to extend these methods to mobile aerial agents (MAAs) such as drones [7,8].

However, most of the work involves imprecise robot localization in which the algorithms and control scheme themselves are used to overcome this limitation. My research project is focused on creating and implementing a more precise method for drone relative-localization which also accounts for the strict communication limitations associated with small drones. Furthermore, rather than using an array of cameras to search for neighboring drones, a single 360º spherical camera will be used.

In the aforementioned areas, the Robotics group has extensive experience and an infrastructure ready to host experimental studies with the innovative algorithms to be developed during this project.

III. Problem Statement

This research aims to create a collaborative multi-UAV system with coverage control that avoids using the communication channel for robot localization. Instead of the transmission of coordinates the UAVs will use visual identification to estimate the pose of the neighboring drones. Initially this will be done by locating fiducial markers that will be attached to each of the agents. However, the final solution aims to be more generalizable and uses a deep learning based computer vision approach to identify surrounding drones. This would eliminate the need for direct transmission of location information between the UAVs in the system. Finally, appropriate coverage control algorithms are implemented such that the target area is split optimally.

However, the proposed solution also has a limitation which is the requirement of the neighboring UAVs being in the line-of-sight of each other. Thus, its efficiency can be hindered in a complicated terrain were the device's vision is impaired. To resolve this issue, each UAV will be equipped with a spherical camera capable of monitoring the environment with a 360° Field-of-View (FOV). The processing of this distorted spherical image in identifying any target drones requires extensive computational capabilities which will be catered towards by utilizing on-board graphical processing units (GPUs).

IV. Solution Methodology

To create the desired multi-UAV system requires equipping each drone with a 360° FOV camera that is capable of streaming high definition spherical video.

Rather than rotating a linear array camera [9], the appropriate full spherical images can be generated by a set of two fixed cameras each equipped with a fisheye lense. By using the overlap of the resulting FOVs it is possible to combine the wide-angle hemispheres to make a single image [10]. Such a camera from the Robotics lab can be seen in Fig. 1.

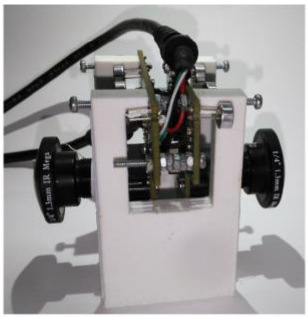

Fig. 1. A spherical camera with two fixed fisheye lenses

Increasing the quality of the video output is also key as a clearer image will allow the UAV to identify targets more precisely at a greater range. In addition, as the effectiveness of this visual system relies on a short response time, an off-the-shelf camera (Ricoh Theta V 360°) will be used. This device can rapidly stitch the two hemisphere-images without overloading the computer unit, resulting in a live 4K video stream.

Fig. 2. Mapped single-plane spherical image

The recorded spherical video feed will then be flattened to produce single projected wide-angle images. An example of the output can be seen in Fig. 2. This can be modelled in a number of ways such as by introducing spherical coordinates or by applying a sensor related coordinate system [10]. From the constructed image the system needs to be able to infer whether there is another UAV in its FOV. This process will be performed using two different methods. Firstly, the initial stage prototype will utilize fiducial markers such as ArUco markers to instantly recognize the presence of any other drones. This can be accomplished by placing the markers on the UAVs that are part of the swarm and scanning for them on the projected image received from the camera allowing for instantaneous identification. Fig. 3 shows a drone from the NYUAD Robotics lab mounted with such markers. However, while this approach has the advantage of being accurate and quick to implement it makes generalizing to other multi-UAV systems difficult as all the drones need to be fitted with markers.

Fig. 3. Drone mounted with ArUco fiducial markers

Consequently, the second solution uses deep learning and computer vision to identify nearby UAVs thereby eliminating the need for any predetermined markers. By training a convolutional neural network architecture on a large scale set of images containing UAVs the system aims to identify any type of drones in its FOV. One of the key challenges to implement this approach is creating an accurate model that is able to identify targets from the distorted wide-angle images that result from projecting spherical images onto a single flat plane. A naive approach would be to repeatedly project the viewing sphere to all tangent planes, however, this would be too computationally intensive for our project. Thus, the system would need to make use of a novel approach which learns to reproduce the flat filter outputs on 360° data while being sensitive to the varying distortion effects across the viewing sphere [11]. This is shown to yield superior results in accuracy and cost compared to training on the images directly. Therefore, the final system would incorporate this deep learning based generalizable system.

Once the system identifies the presence of another UAV in its FOV, it will need to compute their relative pose. Whether using fiducial markers or computer vision this stage can be simplified to a Perspective-n-Point (PnP) problem in which it is necessary to determine the rigid-body transformation (distance and orientation) from the identified observed features on the rigid body (markers). Nevertheless, marker detection is a computationally heavy process especially for high resolution images and since our system needs to operate in real-time this can pose challenges. However, methods such as correctly selecting the most appropriate scale for detection, identification and corner estimation can be used to speed up the detection of markers [12].

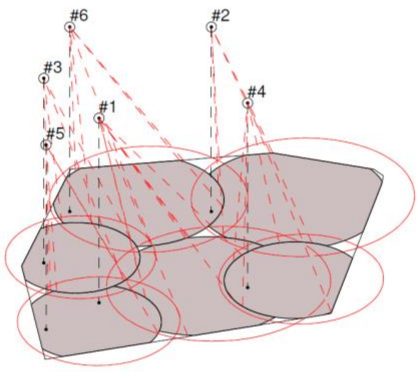

Fig. 4. Paritioning of the area of responsibility

Finally, after the UAV relative localization phase, the project will focus on establishing efficient multi-agent cooperative coverage control. This will be constructed in a distributed manner to make the system more robust and less susceptible to failure. For the first prototype it will suffice to split the target area into 3D-Voronoi cells and assign responsibilities to the various agents accordingly. Furthermore, for this project it is assumed that the total coverage area is known. This process is visualized in Fig. 4 as the bounded target area is partitioned

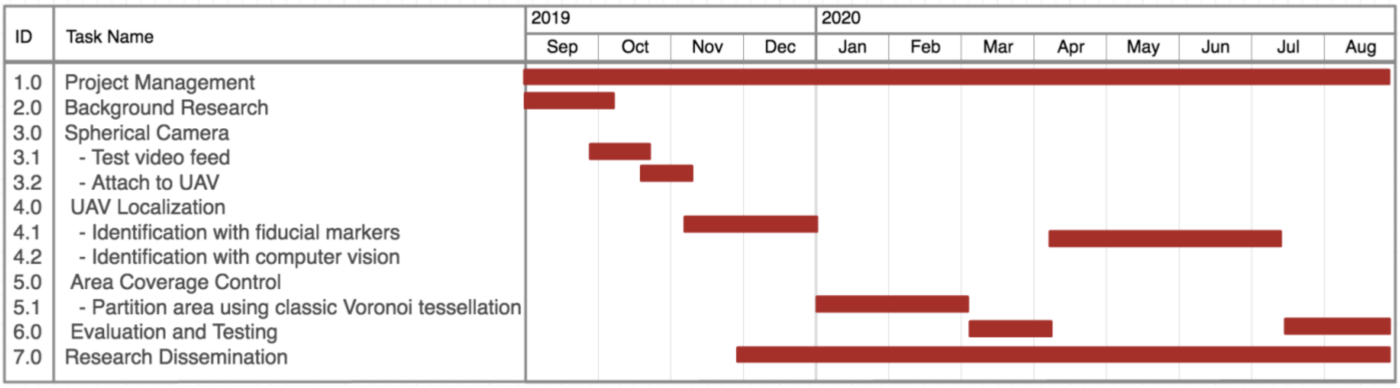

Table 1. Gantt graph – Project timeline

amongst six drones. If possible, more involved algorithms can be introduced later to optimize the splitting of the target area such as using a probabilistic model [13] or the Additively Weighted Guaranteed Voronoi diagram [6]. A next step would also include a control scheme for non-convex domains [14]

V. TIMELINE AND ANTICIPATED DELIVERABLES

Table 1 is a Gantt chart breakdown of research timeline A general research timeline and work breakdown structure is summarized by the Gantt chart in Table 1. The whole project is divided into three major phases: (1) Spherical camera configuration (2) UAV Localization (3) Area Coverage Control. The final solution will effectively combine these three elements into a working prototype and the results will be drafted for publication.

VI. FACILITIES AND RESOURSES

All the equipment required for the successful completion of the research is available in the NYUAD Robotics lab. This includes the NYUAD UAV testing arena in the Kinesis Motion Capture CTP, shown in Fig. 4, where it is possible to fly and test the drones effectively. Similarly, the Core Technology Platform has already acquired the necessary motion capture cameras needed to test and verify the suggested project.

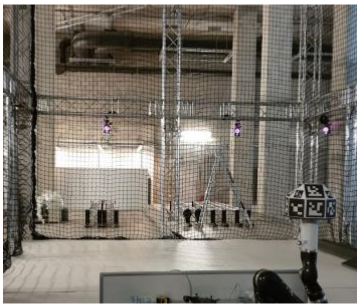

Fig. 4 NYUAD UAV testing arena

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