Proceeding of the IEEE
International Conference on Robotics and Biomimetics
Dali, China, December 2019

A Cooperative Aerial Inspection System with Continuable Charging Strategy*

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***Abstract*— Compared to a single flying robot, the swarm can significantly enhance robustness and capability in real-world missions. However, the overall flight duration of such system is still heavily constrained by the energy system, typically composed of lithium batteries. To cope with this issue, this paper develops an autonomous mobile charging station for the aerial swarm system to improve the endurance so that the system satisfies the need for the long-term mission such as surveillance and monitoring. The mobile charging station has the ability of environment perception and obstacle avoidance. On this basis, a charging module with multiple contact points is developed, and a motion tracking algorithm is proposed accordingly to support precise landing on the charging module. To further improve the flexibility in on-going real-world missions, a charging schedule and an area coverage policy are also proposed. A prototype system is built to verify the effectiveness of this system and experiments demonstrate the system could cover an area of interest completely and efficiently.**

***Index Terms*— Swarm, autonomous UAV system, mobile charging station, visual positioning**

I. Introduction

At present, drones have been widely used in the mission of inspection and surveillance, where long-term observation and data collection over a certain area is required [1]. However, a single drone's capacity is fairly limited. First, the endurance of the drone is rather short due to the low energy density battery. Second, the number and quality of sensors carried by a single drone is limited by its payload [2], thus the robustness of applying these sensors is questionable. Last, the drone's computing power is not abundant so that complicated tasks such as intensive image processing are not feasible to deploy on the drone. So a single drone cannot satisfy mission requirements in some cases [3].

To cope with the issue of capacity, drone swarms have been deployed in the mission of large area coverage and continuous surveillance of location of interest. Many studies focus on efficient communication within the swarm and the cooperation of agents so that they could act as a unity [3]. Meanwhile, the endurance of the drone swarms undermined by battery life [1], [4] also arises researchers' interest. To solve this problem, a whole system including the charging station on the ground has been developed [4]–[7] to increase the mission time of the swarms as long as possible without human intervention.

Many technique details of the autonomous charging system have been explored in literature. To decide the sequence of landing under various constraints, the optimization of the scheduling of charging [8], [9] has been studied. To facilitate the landing process of the drone, vision-based precise landing [1], [10] on the charging platform based on the bottom camera carried by the drone has been developed. After landing, different charging schemes have been applied to ensure efficient charging. The mechanism of charging includes wireless power transfer which allows for imprecise landing on the charging station [4], [11], contact-based charging pad requiring accurate landing [1], [2] and battery swapping system [7], [12] which is kind of complicated in mechanical structure but is much faster.

Based on various available techniques concerning autonomous charging, a relative complete framework of the charging system for the long-duration autonomous operation has been proposed [1]. Furthermore, reference [13] has explored the combination of both stationary and mobile charging stations.

However, the stationary charging system in [1] faces great disadvantages in terms of flexibility. Each drone must return to the charging station in low battery power, thus limiting the range of the whole system. Intuitively, the farther the inspection area is, the more time the drone spends on the way, which indicates the inefficiency caused by the inflexibility. Although [13] introduced mobile charging stations, it focuses on the simulation of the scheduling algorithm rather than the framework of the whole charging system.

To take advantage of the flexibility of mobile charging station and implement the framework of mobile charging for UAV, in this paper, we propose an autonomous unmanned

*This work is partially supported by the National Natural Science Foundation of China (Grant No.51605282, 51975348) and National Science and Technology Major Project (2017ZX01041101-003).

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978-1-7281-6321-5/19//$31.00 ©2019 IEEE

system, including mobile charging stations which carry the drone swarm, charging pads, and an observation system that provides visual positioning for drones so that the system can even be deployed in an area without GPS positioning.

Our key contribution is to propose a complete framework that combines the drone swarm with UGV-based mobile charging stations and that automates the mission cycle, including taking off, complete area coverage, vision-based positioning, landing, and recharging. We demonstrate this framework using four drones and a mobile charging station in the indoor environment. In the following chapters, we explain the key components of the framework in section II, followed by experiments in section III and conclusions in section IV.

II. System Components

A. System overview

The whole system consists of two major parts: a swarm of drones and mobile charging stations. The visual markers are attached to each single drone for positioning, and the landing gear of the drone is specially modified to adapt to contact-based charging. The mobile charging station is a highly integrated platform, including contact-based charging pads and power supply, a computer for data processing, a camera for ground-to-air observation and positioning, devices for communication with drone swarms and other sensors. The framework of the system is shown in Fig. 1.

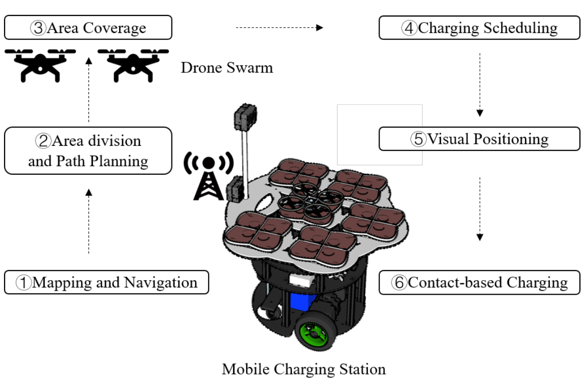


Fig. 1: The framework of cooperative system

To deploy the system, firstly mobile charging stations arrive at the area of interest, carrying a swarm of drones on board. Then drones take off and execute the planned mission and drones of the dynamic number completely cover the area. Meanwhile, mobile charging stations not only maintain communication with drone swarms but sense environment via sensors using SLAM program and avoid obstacles. During the mission, drones in low-battery state return to mobile charging stations according to the scheduling program. In the landing process, the ground-to-air observing system on the mobile charging station determines the position of the drone by identifying and positioning the visual markers on the drone and guides the drone to land precisely on the contact-based charging pad.

B. Mobile charging station

The mobile charging station is based on a UGV platform and integrates a variety of modules, including contact-based charging pads and corresponding power supply, a powerful computer, ground-to-air observation systems, antennas that communicate with drone swarms, and sensors including cameras and odometers for mapping and navigation.

The mobile charging station plays an integral role in the mission. First, the mobile charging station could accommodate several drones that park on the charging pad and transport them to the designated area. Second, it provides real-time positioning for drones and communicates with them and plans the mission as commander center. Third, drones land and recharge on it as scheduled and thus the longer mission time is achieved. Besides, the mobile charging station itself could sense the environment, making autonomous navigation in a complex environment possible. Multiple mobile stations can work cooperatively within an area, increasing the capacity of the system.

The flexibility of mobile charging has to be emphasized. The fact that both the drone in low battery state and the mobile charging station can move toward each other means a shorter time for a drone to return for recharging compared to the stationary charging station. Also, an emergent landing of the drone can also be handled if the mobile charging station moves toward the drone in need.

Mobile charging stations have the ability to navigate through the environment with obstacles. Based on the grid map, a sample-based path planning based on the work of [14] is performed. A cost function in [14] is applied to rank different path given a goal point to reach.

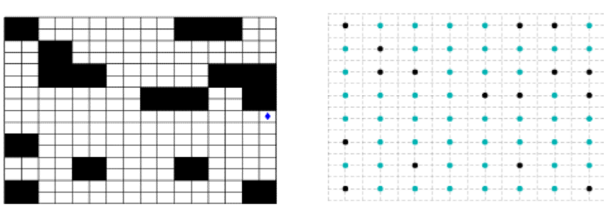
$$J_i = \underbrace{k_1\phi^2_{last,,i}}_{Stagecost} + \underbrace{k_2\theta^2_{goal,i}}_{Terminalcost} \quad (1)$$

The cost function in (1) is divided into two parts: stage cost and terminal cost. In stage cost, $\phi_{last,i}$ is the angular difference between the direction of planed path i and the previously selected direction. This cost prefers a trajectory with a smaller jerk, thus preventing the robot from aggressive movement and making the robot stable. In terminal cost, $\phi_{goal,i}$ is the angular difference between the direction of planed path i and that of the current position pointing to the final target. This cost ensures that the robot tends to choose a trajectory that can move toward the target.

C. Complete coverage algorithm with dynamic number of drones

With mobile charging stations to prolong the endurance of drone swarms, long term mission is possible. We develop a complete coverage algorithm for drone swarms, which aims at a scenario of surveillance over an area.To completely cover a certain area with drone swarms, a method that combines an area division algorithm and a path planning algorithm is applied for the problem.

To fully utilize the capacity of drone swarms, the mission area should be divided into several sub-regions according to the initial position of the swarm [15] so that they could execute the mission simultaneously. The sub-region should satisfy two requirements: (1)the sub-region is continuous and the initial position of the robot lies in the corresponding sub-region; (2)all sub-regions are almost equal in size. For area division problem, DARP (Divide Areas based on Robot's initial Positions) [16], a discrete algorithm, is an ideal candidate. The algorithm processes an area that has been divided in advance into discrete grids equal in size (see Fig. 3(a)) and classifies center points of these grids into several sub-regions (see Fig. 3(b)). However, DARP cannot always find a feasible solution to the area-division problem efficiently. The reason is that the DARP algorithm allows discontinuous regions in the iteration and does not guarantee that the area of discontinuous regions is decreasing. Therefore, sometimes it cannot find a feasible solution within a given number of iteration time. To avoid the inefficiency caused by this, edge detection is applied to the algorithm. If the edge of the region's growth can be confirmed, the sub-region will not grow across another sub-region, thereby avoiding unnecessary discontinuities. This approach will speed up the convergence of the area-division algorithm.



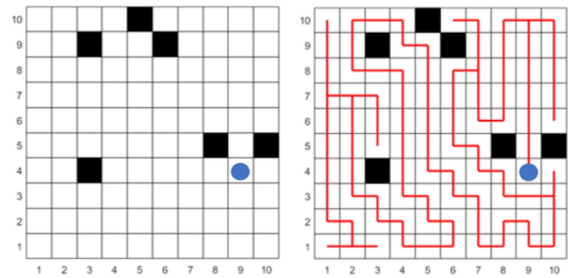
(a) An area divided into grids (black blocks represent obstacles and white ones represent free space)

(b) Center points of grids that DARP algorithm needs to classify into sub-regions

Fig. 2: Discrete area-division algorithm

Based on the partitioned regions of the above algorithm, the STC (Spanning Tree Coverage) algorithm [17], [18] is applied to every sub-region so that the shortest spanning tree including center points of every grid could be generated. Once the spanning tree is obtained, the trajectory the drone should follow is just the envelope of the tree (see Fig. 3).

To apply the DARP and the STC algorithm to drone swarms, a pseudo-decentralized control framework is used in the control scheme. As shown in Fig. 4, each drone has an independent robot controller while it accepts advanced commands from the commanding center. Each robot controller corresponds to a distinct thread in the computer and a



(a) A sub-region that the STC algorithm processes

(b) A spanning tree connects all center points of blocks of free space

Fig. 3: STC algorithm applied on a sub-region

drone in the real world. The commanding center executes the the DARP and STC algorithm. This framework has several advantages. First, it can be utilized in a swarm with an uncertain number of drones. The adding or leaving of a drone corresponds to creating and destroying different threads in the program. And the commanding center just needs to replan the path of the new swarm. This is vital because the number of drones varies according to the charging schedule. Second, the relative independence of each drone's controller means the robustness of the drone swarm will be improved because the failure of an individual drone would not significantly affect other individuals. Third, the adjustment of the individual control pattern only requires a change of its controller, which enables convenient parameter adjustment frequently encountered in experiments.

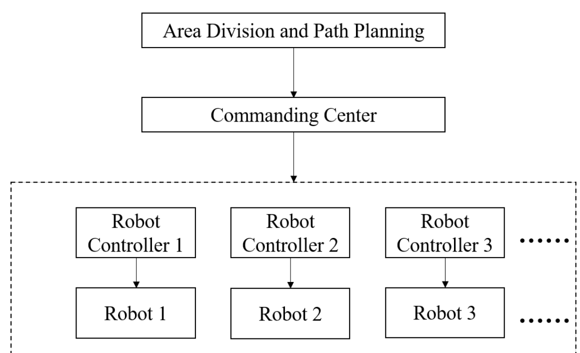


Fig. 4: Pseudo-decentralized control framework

D. *Charging scheduling algorithm*

The charging scheduling algorithm available for the UAV swarm can be divided into two categories: centralized and distributed.

In the centralized algorithm presented in [19], each drone can obtain the battery information of all other drones. The drone with the least battery power would be charged first. Assuming that the power of each drone is the same at the beginning. In this case, in order to make the endurance of the swarm as long as possible, it is necessary to make the average power consumption rate of each drone as close as possible. The most ideal situation is that all drones exhaust their battery and land at the same time . The charging time of each drone could be expressed as (2).

$$t=\left\lfloor\frac{\max\left(E_{a_i}^{j}\right)-OP(h)}{\alpha_t\left(N_s-1\right)}\right\rfloor \tag{2}$$

$E_{a_i}^{j}$ means the remaining battery power of the drone a_i at time j. $OP(h)$ represents the energy cost of a drone climbing up to altitude h or landing to the ground from altitude h, and α_t is the energy consumption of a drone in the working state per time slot t. N_s means the number of drones.

In the distributed algorithm, each drone only has access to battery information of several drones nearby and it will decide whether to charge at a certain time. Each drone will inform surrounding drones whether it plans to land for charging. If the charging station is found to be occupied, the drone will resume its mission; otherwise, the drone will land on the charging station. Probability-based and game theory-based are two kinds of distributed algorithms.

For the distributed algorithm based on probability in [19], the charging time is calculated by (3).

$$t=\left\lfloor\frac{E_{avg}^{|NE|}-2OP(h)}{\alpha\left(N_s-1\right)}\right\rfloor \tag{3}$$

Equation (3) takes the battery state of the surrounding drones into consideration. $E_{avg}^{|NE|}$ represents the average remaining battery power of $|NE|$ drones nearby. After the charging is over, the drone will return to the area where it was to continue the mission.

In the probability-based algorithm, the drone has to execute each action with an excitation function $S(T)$, which indicates the degree of necessity to perform a certain action at time T. The probability p_i to perform this action can be calculated by (4).

$$p_i=\frac{S(T)}{\theta_i+S(T)} \tag{4}$$

θ_i represents the response function which indicates the ability of the individual i to perform a certain action.

For the distributed algorithm based on game theory, each drone has two states at a certain time: flying and charging. The flying drone faces two options: to continue flying or to land on the charging station, while the charging drone also faces two choices: to take-off or to continue charging. Because the battery information of drones could be shared among the swarm, this problem can be modeled and solved by game theory, which was discussed in [9].

E. Ground-to-air observing module

Visual positioning has been used in literature to enable the drone to land accurately on the charging station. A drone equipped with a camera and visual markers attached to the charging station is the most common solution. This raises several problems. First, the camera is only functional during landing but useless in other cases, which undermines the payload and the battery life of the drone. Second, the image processing during visual positioning usually requires intensive real-time computation, but the limitation of battery life and payload of the drone makes abundant computing power unavailable. Therefore, the camera on the drone for visual positioning is more or less a burden. Third, because the marker is attached to a stationary charging station, in order to identify and locate the visual marker, the drone should be equipped with external positioning devices so that it can hover near the charging station and the visual marker is in the field of view of the drone camera.

To solve the above problems, we applied camera-based positioning equipment on mobile charging stations and attached the visual marker to the drone instead. The design has the following benefits. First, the drone carrying visual markers significantly lighter than a camera has a longer battery life because markers do not require energy or computing power anymore. Second, drones could be observed in a wide range and angle. Because the observing system is deployed on the flexible mobile charging station, the scope of the observing system to identify the drone has been enormously enlarged. Third, the observing system not only provides positioning during landing but could locate drones during flight as well. Moreover, several mobile charging stations equipped with the observing system scattered in an area could achieve continuous observing and positioning for drone swarms during the mission, even in the absence of GPS and other external positioning methods. Last, more complex but effective positioning algorithm requiring more computing power could also be run on the mobile charging station due to its abundant computing power.

To achieve the above scheme, the visual markers are attached to the drone so that the camera could capture them due to their highly reflective characteristics in the common environment. Visual positioning algorithm based on binocular camera has been used to calculate relative position between the camera and the drone.

Assume that the coordinate of a point in the world frame is $P=[X,Y,Z]^T\in R^3$, and it is projected on the screen of a camera with a pixel coordinate $P'=\left[\begin{array}{c} u,v \end{array}\right]^T\in R^2$. According to the perspective principle, the transformation from P to P' can be expressed as (5), where K is the internal parameter matrix of the camera.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \frac{1}{Z} K \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \tag{5}$$

For a binocular camera, the pixel coordinates P_{left}, P_{right} of the target point can be obtained respectively using (5). Suppose the target points coordinate in the world frame is $P = [X, Y, Z]^T \in R^3$, and its depth in the left and right camera is S_{left} and S_{right}. Then there is an Epipolar Constraint between P and P_{left}, P_{right}.

$$P = f_{left} S_{left} K_{left}^{-1} p_{left} = f_{right} S_{right} K_{right}^{-1} R p_{right} + K_{right}^{-1} t \tag{6}$$

In (6), K_{right} is the internal parameter matrix of the right camera. R is the attitude matrix of the right camera under the left one and t is the translation vector of the right camera under the left one.

To solve (6), left multiply on both sides of the equation, and then the least-square solution of s_r can be found. With s_r, s_l, R can be solved eventually.

$$f_l s_l \hat{p}_l K_l^{-1} p_l = f_r s_r \hat{p}_l K_r^{-1} R p_r + \hat{p}_l K_r^{-1} t = 0 \tag{7}$$

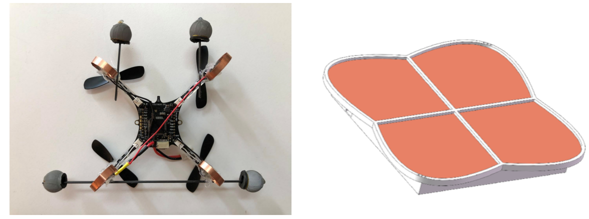
To align the point P_{left} and P_{right}, feature points based on two-dimensional code is introduced. And raw position obtained through binocular positioning will further be processed by the Kalman filter to get more reliable position estimation. This will be explained in detail in III-D.

F. Contact-based charging module

To charge drones efficiently, contact-based charging is applied in the system. Compared to wireless charging, contact-based charging is more efficient and requires less charging time, which prolongs the mission time of drones and thus improves efficiency. Compared to the battery-swapping scheme, which requires a well-designed and complicated mechanical structure to swap the battery, contact-based charging is more convenient for mobile charging stations to carry and avoids the problem of data loss caused by restarting the drone during battery swapping.

The design of the charging system was inspired by [2]. First, conductive copper rings are attached to the bottom of the drones landing gear, which has been connected to the positive and negative poles of the battery respectively and would be able to contact the charging pad after landing. The weight of the drone would compress copper rings after landing, which results in closer contact with the charging pad and less contact resistance. The drone with copper rings for charging is shown in Fig. 5(a).

Three measures have been taken for robust charging to avoid the short circuit. First, the ground-to-air observation system enables the drone to lands as accurately as possible on the charging pad, thus meeting the positive and negative requirements for charging. Second, anti-reverse protection has been applied. Third, the size and the shape of the charging pad have been specially designed to ensure that never will both poles of battery contact with the same pole of charging pad. The structure of the charging pad is shown in Fig. 5(b)



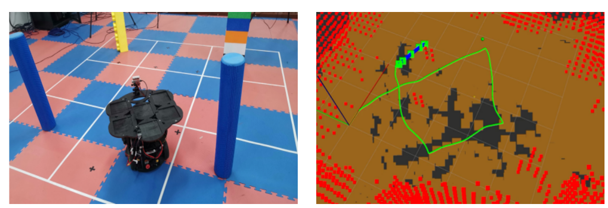
(a) Crazyflie with copper charging rings and markers (b) Contact-based charging pad

Fig. 5: The design of the charging module

III. Experiment results

A. Mobile charging station

To test the performance of path-planning and obstacle avoidance, the experiment was done in an indoor square area of 4x4 meters with 4 obstacles. The goal point was set on edges of the square repeatedly. Once the mobile charging station reaches a goal point, the next one was set. The mobile charging platform was operated in the area safely during 2 minutes long test. The test environment is shown in Fig. 6(a) and the grid map and the trajectory of the mobile charging station is shown in Fig. 6(b).



(a) Test environment of the obstacle-avoidance algorithm (b) Grid map and trajectory of the mobile charging station

Fig. 6: Mobile charging station experiment results

B. Complete area coverage algorithm

To demonstrate the complete area coverage algorithm, a simulation and an indoor experiment were done.

In the simulation, four robots were placed at a random initial position in a square area, and then they completed the area coverage task by applying area division and path planning algorithm. Fig. 7 shows the process of area coverage. The blue area represents the area that has been covered by the robot sensor. By the end, the entire target area is covered.

In the indoor experiment, 4 drones performed area coverage tasks within the square area of 16 square meters. Fig. 8

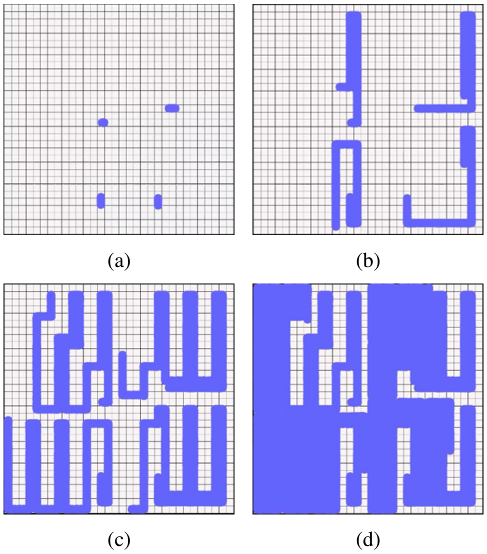


Fig. 7: Complete area coverage process in simulation

shows the process of the covering task. The top right corner of sub-figures indicates the trajectory of 4 drones.

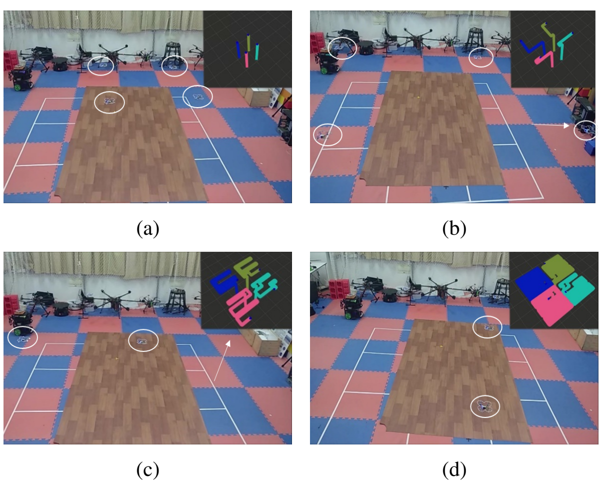


Fig. 8: Complete area coverage process in experiment

C. *Scheduling charging algorithms*

Three kinds of scheduling algorithm mentioned in section II-D were simulated in OMNet++5.5 [20] with a network of 15 drones. The simulation simplifies each drone into a node that can communicate with the surrounding drones. Drones battery power and state change over time. The simulation only considers the topology of the communication network and does not consider the actual motion of the drone. The parameters of the drone are based on Crazyflie, a micro quadrotor with a single-cell lithium-ion battery.

The simulation results are shown in Fig. 9 and Fig. 10.

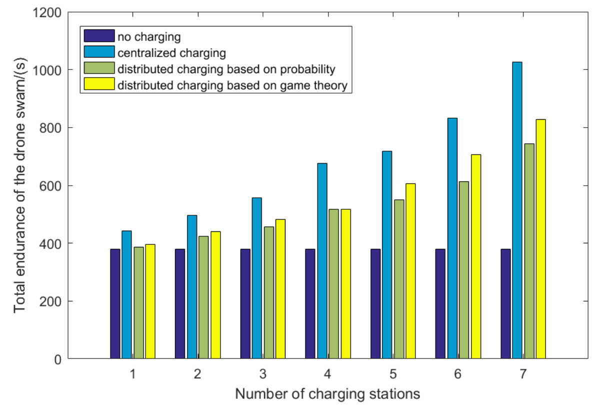


Fig. 9: The endurance of the swarm applying different charging scheduling algorithms

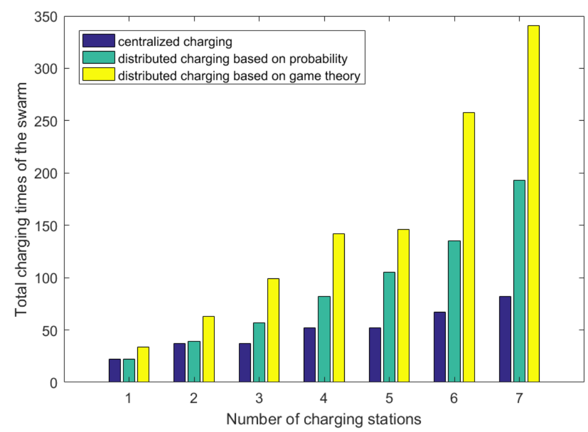


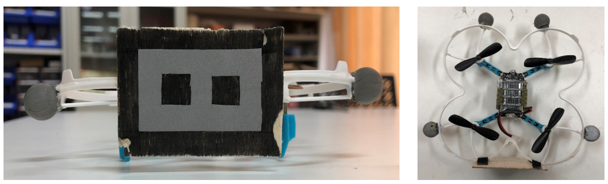
Fig. 10: Total charging times of the swarm applying different charging scheduling algorithms

Three algorithms have a positive effect on extending the endurance of the drone swarm. The more the number of charging stations, the more obvious this effect is. Among them, the scheduling theory based on game theory has the most total number of charging times. As far as endurance is concerned, the effect of the centralized algorithm is better than the other two, and the more the number of charging stations, the more prominent the gap between them.

The simulation results verify the optimality of the centralized algorithm. For distributed algorithms, although the game theory-based scheduling algorithm is better than probability-based one in terms of extending endurance, its large number of charging times undermines its efficiency because a considerable part of the time and energy is spent on landing and taking-off action.

D. Ground-to-air visual positioning performance

Binocular visual positioning experiments were performed in an indoor environment with the VICON system. The camera used is Intel's D435 binocular camera, and the two-dimensional code with reflective material is used for feature point recognition (see Fig. 11(a)). When acquiring feature points, contour extraction is adopted. The center point of the rectangle on the two-dimensional code is taken as the feature point for positioning. At the same time, the visual markers are attached to the drone to be simultaneously positioned with VICON (see Fig. 11(b)).



(a) Side view (b) Top view

Fig. 11: Minifly with two-dimensional code and visual markers

VICON's positioning results are regarded as the ground truth. The experimental results of the positioning are shown in Fig. 12. Positioning results include VICON positioning data as ground truth, raw data of camera positioning, processed camera data using low pass filter and Kalman filter respectively.

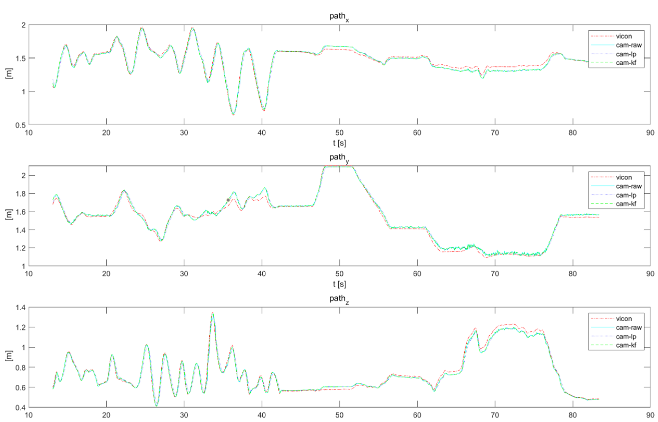


Fig. 12: Positioning results

To demonstrate the ability of the ground-to-air observing system, an experiment was done in the indoor environment. In the experiment, a drone took off from the ground and landed on the charging pad of the mobile charging station. The process is shown in Fig. 13.

E. Whole system experiments

With all components tested above, a prototype system has been developed to verify the autonomous framework.

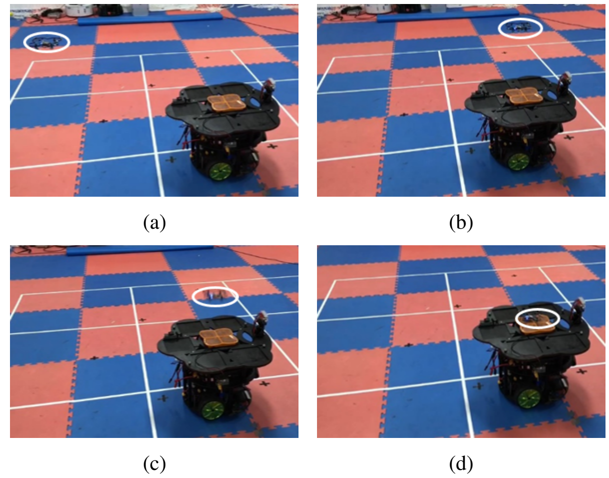


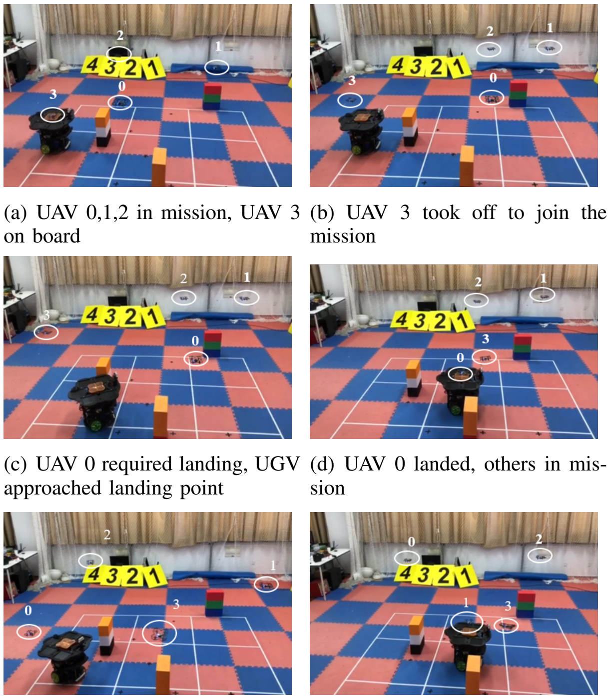
Fig. 13: Landing process of drone using observing system

The entire system consists of a mobile charging station and 4 drones. Because the relatively small mission area and the number of drones, commutation between drones and mobile charging stations is robust and centralized charging scheduling algorithm was applied in the experiment.

In a 16 square meters area with obstacles, the mobile charging station cruised and autonomously avoided obstacles, while four drones on charging pads took off to perform area coverage tasks. During the mission, four drones alternately landed on the mobile charging station for charging. When a drone issued a charging request, the mobile charging station would move to the center of the mission area. After the drone landed on the charging pad, the mobile charging station continued its cruising. The process of the experiment is shown in Fig. 14.

IV. Conclusions and Future Work

We introduce a framework combining a swarm of drones and mobile charging stations, which could work cooperatively in a long period in an area of interest. Components of this autonomous system are elaborated in detail. Contact-based charging modules are designed to ensure reliable and efficient charging for drones. Charging scheduling algorithms are applied to prolong the endurance of the drone swarm. The ground-to-air observing system provides large-scale positioning for drones during the mission and landing process. A complete coverage algorithm is introduced for the drone swarm to cope with the scenario of inspection. Highly integrated mobile charging stations could navigate in an environment with obstacles and transport drone swarms to the mission area. A series of experiments were done to demonstrate the performance of these components. A complete experiment in an indoor environment with one mobiles charging station and four drones shows that the prototype system could complete the planned mission circle.



(a) UAV 0,1,2 in mission, UAV 3 on board

(b) UAV 3 took off to join the mission

(c) UAV 0 required landing, UGV approached landing point

(d) UAV 0 landed, others in mission

(e) UAV 0 took off after charging

(f) UAV 1 landed, others in mission

Fig. 14: Cooperative area coverage mission experiment

We plan to improve the stability of system components and apply the system to the mission of coverage of an outdoor area and further demonstrate its performance. Also, experiments that compare the charging performance of our system with that of the other in the same scenario are needed.

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