On Path Planning Strategies for Networked Unmanned Aerial Vehicles

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***Abstract*—In this paper, we compare deterministic and probabilistic path planning strategies for an autonomous unmanned aerial vehicle (UAV) network, where the objective is to explore a given area with obstacles and provide an overview image. We present both online and offline implementations of the algorithms as alternative solutions, where applicable, and analyze the performance of the offline implementations. Results illustrate the benefits and drawbacks of different planning strategies and provide insight into which strategy should be taken, given the constraints of the application of interest.**

***Index Terms*—UAV networks, wireless sensor networks, mobility, coverage**

I. Introduction

Networked small unmanned aerial vehicles (UAV), sometimes called microdrones, have recently drawn the interest of several researchers focusing on topics such as control engineering, communication networking, mission planning, and image processing. In this paper, we consider a network of UAVs, where each UAV is equipped with an on-board camera, and the objective is to explore an area of interest by taking several pictures and provide an overview image in an efficient manner.

In this paper, we are interested in path planning methods for a UAV network. Generally, path planning for robotics has two main components [1]: area decomposition (e.g., static, dynamic) and routing (e.g., deterministic, adaptive, cooperative). Several centralized and distributed planning methods have been proposed using combinations of these components. The benefits and drawbacks differ in terms of adaptability, scalability, robustness, path completion times, and other metrics. In this work, we compare and contrast deterministic and probabilistic path planning methods in terms of achievable coverage, number of pictures taken, path planning and execution times, for different area sizes and number of UAVs. More specifically, we study two path planning methods and their variants: 1) a method that uses a *static* area decomposition [2] and a simplified *Capacitated Vehicle Routing* [3], where a traveling salesman problem model is utilized, and 2) a method with *no* area decomposition and *adaptive* routing [4].

Results show that both approaches have their benefits and drawbacks. Since the deterministic approach aims to minimize the number of pictures taken to cover a given area, given enough UAVs, full coverage can be *guaranteed*. However, this approach requires prior knowledge of the area and has limited adaptability to changes. On the other hand, the probabilistic approach has the benefit of potential online implementation, and hence, immediate reaction to changes. For a fair comparison, we study the offline implementation of the probabilistic approach.

There are several planning strategies proposed for ground robots [1], delivery systems [5], autonomous high-speed, fixed-wing UAV networks [6], or mobile sensor networks [7] with different objectives and constraints. Applications range from snow removal, lawn mowing, floor cleaning, to surveillance, mobile target tracking, chemical or hazardous material detection and containment, or to any combination of localization and navigation problems (see [8], [9], [10]). While some algorithms use prior information and have exact or partial decomposition of the areas, others use sensor-based information in unknown environments to make navigation decisions. Algorithms exist that try to minimize the path traveled or time or energy required to achieve a goal. These different schemes have some common building blocks, such as static or dynamic area decomposition, cooperative or non-cooperative actions, individual or collective decisions, static or adaptive behavior. Therefore, in this paper, we study two different approaches that consider some intuitive combination of these building blocks.

The remainder of the paper is organized as follows. The system model and metrics of interest are given in Section II. The methodologies are introduced in Section III. Results are given in Section IV and the paper is concluded in Section V.

II. System Model and Performance Metrics

The monitored area consists of a bounded geographical region with no-fly zones. The UAVs take-off from a home-base, fly at a certain height, and return to home-base.

A. System Model

Observation area is the region of interest without obstacles.

Forbidden area consists of the collection of obstacles and no-flight zones in the region of interest, where the safety requirements are taken into account. To determine the forbidden area, first the obstacles are grown according to the UAV wingspan. This step is necessary for the area decomposition (i.e., picture point generation) step of the *deterministic* path planning algorithm to prevent the UAVs from crashing into obstacles. For the *probabilistic* path planning algorithm, on the other hand, the UAVs detect the obstacles in flight.

The additional system parameters are the number (N), velocity (V), and maximum flight time (T) of the UAVs, and the ground picture coverage of a photo taken from a given flight height using certain camera specifications.

B. Performance Metrics

We study the deterministic and probabilistic path planning methods in terms of the following metrics:

Spatial coverage is the percentage covered area [4]. We are interested in both the observation (C_O) and forbidden (C_F) area coverages.

Path completion time is the time required for all the UAVs to fly their paths. To compute these times, we use a simple UAV model, where each UAV flies on average with 4 m/s horizontal speed and with 3.75 m/s vertical speed for take-off and landing; it takes 6.25 s to take a picture; and the rotation speed is 30^o/s. These values are taken from the specifications of the Microdrone's md4-200 [11].

Number of pictures taken is also a parameter of interest to illustrate the redundancy of a given plan.

Planning time is the time required to generate one plan.

III. Path Planning Methods

A. Deterministic Path Planning

This method assumes prior knowledge of the observation and forbidden areas. The approach is summarized in Algorithm 1. Given the area of interest, number, velocity, flight time of UAVs, and ground coverage of the camera at the flight height, this method first decomposes the area into equal area cells that correspond to one picture and then generates the shortest paths for the UAVs to cover the fixed set of picture points. The picture points are generated using an Integer Linear Program such that the number of picture points are minimized given the area, ground coverage, and possible camera orientations (for details of the algorithm, readers are referred to [2]). Two picture orientations are allowed for simplicity, where UAVs align in north-south or east-west directions when the pictures are taken. Since the complexity of the algorithm increases with the number of potential picture points, we also consider a simplified variant, where the area is partitioned into smaller subareas. The picture points are generated for each partition and the resulting coordinates are merged.

The second step is the routing of the UAVs between the picture points. The problem can be modeled as a Capacitated Vehicle Routing Problem (CVRP), in which a given set of „customers" are visited by a set of „vehicles" with limited „capacity". In our case, the customers, vehicles, and capacity are the picture points, UAVs, and limited battery, respectively. Several heuristics exist for the solution of CVRP. We use a genetic algorithm developed to solve the well-known Traveling Salesman Problem (TSP), which is suitable for the picture point set size and plan time considerations in this paper. For practical reasons (e.g., envisioning limited time for planning a path), we use a simplified multiple-TSP algorithm given the set of picture points. To this end, first, the set of picture points are clustered into groups using k-means clustering such that each cluster can be covered by a single UAV within its maximum

Algorithm 1 Deterministic Path Planning: Variants 1-2

Input: Area of interest, number of UAVs (N), maximum flight time, velocity, ground picture coverage and orientation.
Output: Flight paths; picture points and orientations.

1) *Partitioning*:
   a) For Variant 1 this step is skipped.
   b) For Variant 2: the observation area is divided into partitions of size less than a threshold.
2) *Picture point generation*: Picture point coordinates are generated using an Integer Linear Program, given the partitions from step 1, the ground picture coverage and orientation [2].
3) *Clustering*: *k-means* clustering is used to group picture points, such that each cluster can be visited by a single UAV within its maximum flight time. N largest clusters are chosen.
4) *Routing*: For each cluster, shortest route is generated between the fixed set of picture points using a genetic algorithm based TSP solution.

flight time. If the number of clusters generated is more than the number of available UAVs (N), N largest clusters are chosen to maximize the covered area in a single flight. Then, a genetic algorithm solution to TSP is run for each cluster to obtain the routes for each UAV.

B. Probabilistic Path Planning

This approach assumes no prior knowledge of the area of interest. Ideally, there is no prior area decomposition or an *end-to-end plan*. Therefore, path planning becomes equivalent to routing. In other words, the UAVs are informed of the boundaries of the area of interest and they start from the home-base and take pictures at intervals determined by the ground picture coverage. They continuously sense for obstacles. The path decisions are made during flight based on the available information at a given point in time. To this end, a belief-based movement approach proposed in [4] that makes use of the local physical topology information without global knowledge of the network is adopted. At fixed time intervals, the UAVs sense their environment for neighboring UAVs (e.g., with radio communications). If neighbors are detected, the nodes exchange *location* and *direction* information (provided by GPS). Then, each node computes the *belief* (i.e., probability) that it should move toward a new direction, based on the *node's own observations* and the information from its neighbors. The period for sensing neighbors is chosen based on the wingspan of the UAVs to avoid collisions.

Since the UAVs only utilize local information, the algorithm is robust to environmental and network changes, such as new areas to be covered or UAV failure, and quickly adapts to these changes in a *self-organizing manner*. However, the performance is affected heavily by the vulnerabilities due to communication constraints imposed by the radio-on-board as well as wireless channel dynamics. The impact of communication limitations on the algorithm is part of our future work.

While the method is envisioned for online implementation, for a fair comparison with the deterministic approach, in this paper, we analyze the offline implementation, where the paths are generated using full knowledge of the area of interest and loaded on the UAVs prior flight. It should be noted that

Algorithm 2 Probabilistic Path Planning: Variants 1-2

Input: Area of interest, initial directions, number of UAVs (N), maximum flight time, velocity, ground picture coverage, sensing range and period.
Output: Flight paths; picture points and orientations.

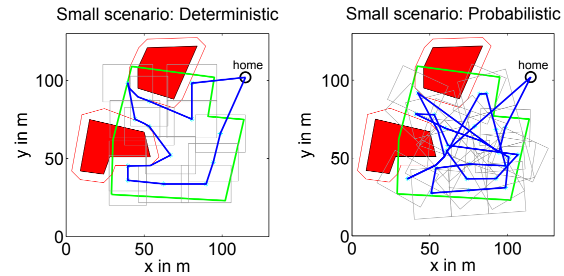
1) *Path generation*: The cooperative flight paths are computed for each UAV using the belief-based movement algorithm of [4].
2) *Picture point generation*: Picture points are generated by sampling the flight paths using the ground picture coverage.
3) *Routing*:
   a) Variant 1: The algorithm returns the computed picture point coordinates from step 2 and the corresponding flight path coordinates.
   b) Variant 2: In this step, the overlaps between the generated pictures are determined and redundant pictures are eliminated.

this is not the ideal way to implement this approach, since it loses its benefits with respect to its adaptivity to environment changes. For an analysis of the online implementation of the belief-based movement algorithm for coverage as well as time-critical event detection and tracking applications, the readers are referred to [4] and [12]. The offline implementation of the variants is shown in Algorithm 2.

Variant 1 of the algorithm is similar to the *online* implementation, where each waypoint is a picture point, i.e., waypoints are separated by a distance less than or equal to a picture size. Once the paths are computed using belief-based movement algorithm of [4], they are sampled at every ground picture size in flight direction and the line segments between the consecutive picture points are computed such that the lines do not cross a forbidden area. Variant 1 is simple and has several benefits, but it also has a major drawback: redundancy. Due to lack of knowledge from other UAVs' coverages, there might be duplicate images, which is both time and energy consuming. While such redundancy might be useful in case of imperfect sensing [13], its analysis is beyond the scope of this paper.

Variant 2 of the algorithm is considered for offline implementation. It is proposed to overcome the potential redundancy of Variant 1. By a simple post-processing of the picture points generated by Variant 1, the overlaps between the pictures are determined and redundant picture points are eliminated from the generated paths. Note that if the UAVs exchange complete history information and continuously build their own map of the environment, an online implementation of this variant is also possible. Variant 2 results in fewer pictures taken than Variant 1 and faster plan generation compared to the deterministic approach.

An example for the paths generated by the Variant 2 of deterministic and probabilistic path planning strategies is shown in Fig. 1 for a small area of interest and a single UAV. The ground picture coverages are also shown (light grey) over the observation area (green) with 2 obstacles (red). The grown obstacle boundaries are also shown. Observe that the path from the probabilistic approach is significantly longer than the deterministic case. But, as will be shown, with a larger number of UAVs where cooperation is possible the difference significantly reduces. Also, the orientation of the pictures for the probabilistic scheme is very random, which is a drawback



(a) (b)

Fig. 1. Generated paths for the small scenario, when $N = 1$

since rotations cost time and energy.

IV. Results and Discussion

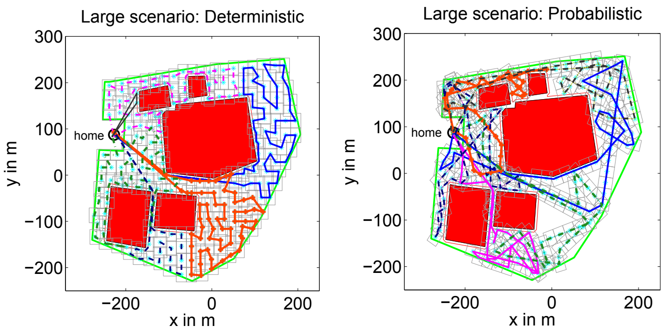
In this section, we evaluate the performance of the deterministic and probabilistic methods via simulations. The results for the probabilistic method are generated over 100 runs. We study several scenarios with different area and network sizes. The simulation parameters are summarized in Table I. We study three area sizes: small (Fig. 1), medium (second quadrant of Fig. 2), and large (Fig. 2).

We allow a certain time duration for plan generations. The deterministic approach variants can return one or no plans at the end of the allowed time (see Table I for plan times). For instance, for the large scenario, Variant 1 of the deterministic scheme cannot generate the picture point locations to be traveled due to the area size. Hence, for this scenario we present results only for Variant 2 of the deterministic algorithm. The probabilistic approach on the other hand can generate multiple plans. To utilize this fact, we use the allotted time to generate as many *virtual* plans as possible and we pick the "best" plan. The definition of "best plan" is clearly subjective but based on the intended goal it is defined as the plan that achieves highest observation area coverage. If multiple plans are generated with the same coverage, we pick the one with the shortest time.

Finally, we assume that the UAVs have a limited flight time of 17 min, which is a reasonable value for current technology. Path plans are generated such that these times are not exceeded and we assume that the UAVs fly only one round, i.e., depending on the number of UAVs parts of the area of interest might not be covered within one flight time.

TABLE I
Simulation Parameters

Parameter	Value
Observation area [m^2]	Small: 4831.89, Medium: 28160.7 Large: 116474
Obstacle area [m^2]	Small: 807.114, Medium: 14277.3 Large: 54270.4
N	$\{1, 3, 6, 9\}$
Maximum V [m/s]	5
Flight time [min]	17
Ground picture coverage [m^2]	24×32
Allowed plan time [s]	20 (small), 100 (medium, large)



(a) (b)

Fig. 2. Generated paths for the large scenario, when $N = 6$

First, we investigate the coverage performance of the different planning strategies. Figures 3-4 show the observation and forbidden area coverages, respectively, versus the number of UAVs. Since the variants for both schemes achieve the same observation area coverage only the C_O's for the second variants are shown in Fig. 3. Observe that the coverage significantly improves for both schemes with increasing N, as expected. On average, probabilistic schemes require a higher number of UAVs than the deterministic scheme to achieve high coverage. While the deterministic scheme aims for full coverage and can achieve it given sufficient N, only probabilistic guarantees can be given for the other scheme. Also observe that for the large scenario the two schemes perform very similar.

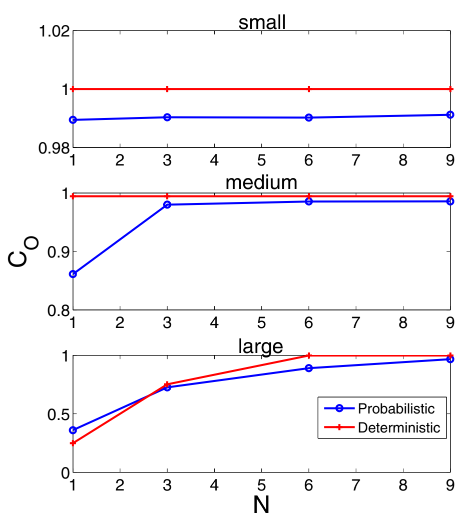


Fig. 3. Observation area coverage versus number of UAVs

Observe from Fig. 4 that the forbidden area coverages are also high. Deterministic scheme achieves the best C_F, since it is also one of the optimization criteria of the picture point generating algorithm. Due to its redundancy, Variant 1 of the probabilistic scheme also achieves a high C_F and approaches that of the deterministic schemes. For the medium and large scenarios the C_F is significantly low, due to both the size of the observation area to be covered (which has higher priority) and also the size of forbidden areas in these scenarios.

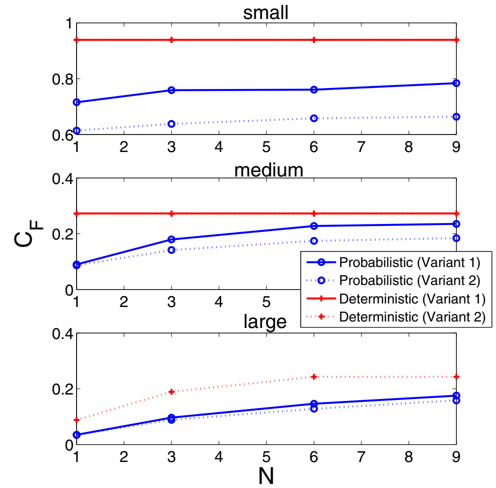


Fig. 4. Forbidden area coverage versus number of UAVs

Second, we analyze the path completion times for all schemes in Fig. 5. They are computed as described in Section II using the specifications of the md4-200. As mentioned above, the UAVs can fly a limited amount of time. Though none of the algorithms are optimized for path completion time, it is still preferable to achieve a given coverage in a short time (e.g., due to energy saving and also for time-critical applications). From Fig. 5 we observe that the coverages presented in Figures 3-4 can be achieved within the flight time for all scenarios. However, observe that for the small and medium scenarios, especially for small N, the deterministic algorithms can complete the path in a significantly shorter time than the probabilistic schemes. In other words, while similar coverage values are achieved for both schemes, the time required to achieve them can significantly differ based on the system parameters. As the area size grows, this difference reduces. The large scenario under study is constructed in a way that the entire allowed flight time needs to be consumed to achieve the presented coverages and hence, for both schemes paths are completed around the same time.

The path completion times consist of not only the mechanical components due to acceleration/deceleration, take-off, landing, and rotating of the UAVs, but also time necessary to take pictures. Fig. 6 shows the number of pictures taken by each scheme. Clearly, both variants of the deterministic scheme result in a lower number of pictures, since they are optimized for it. The difference between the deterministic and the probabilistic schemes can be as high as 100 % depending on the area size and N, which also explains the path completion time and coverage differences of the two approaches. Variant 2 of the probabilistic scheme significantly reduces the number of pictures taken (by half in some cases) compared to Variant 1. However, this approach either enforces offline implementation due to lack of available communication technology or requires feedback from a central station that builds a map of the area from all UAVs or individual map/history exchange between the UAVs for an online implementation.

Finally, we study the time required to generate a plan

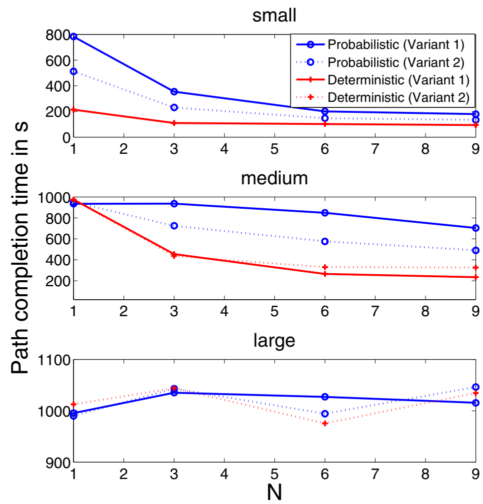


Fig. 5. Path completion time versus number of UAVs

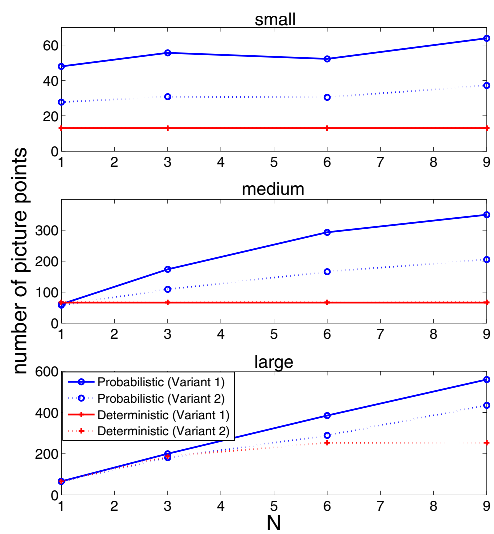
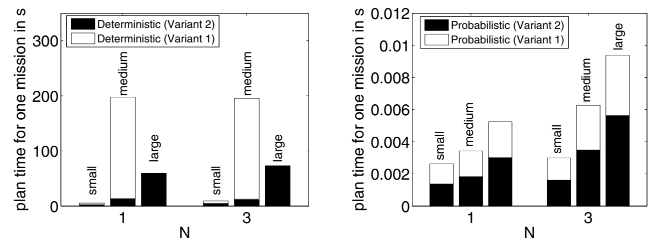


Fig. 6. Number of pictures taken versus number of UAVs

if all algorithms were implemented offline. Clearly, offline implementation might not be possible or realistic if the area to be observed is dynamic or full knowledge of the area is not available beforehand. However, for completeness sake, we present the time required to generate one plan in Fig. 7 (These values are computed by a workstation with an Intel Core i7-870 processor and 8 GB RAM). As mentioned before, for Variant 1 of the deterministic scheme there is no plan generated for the large scenario. Observe that the deterministic scheme can require significantly more computation time than the probabilistic schemes. This implies that if the application is time-critical and not much time is available for planning, i.e., if immediate start of the flight has more priority than a "best" path plan, the probabilistic scheme can be implemented offline to provide a plan right away. If the full coverage of the area within a lower (albeit possibly not the minimum) time has a higher priority, then the deterministic scheme is more acceptable.



(a) Deterministic path planning (b) Probabilistic path planning

Fig. 7. Path planning time versus number of UAVs

V. Conclusion

We illustrated the benefits and drawbacks of deterministic and probabilistic path planning strategies for an autonomous UAV network, where the objective is to explore a given area with obstacles and provide an overview image. Our results show that while the deterministic approach can provide a solution with minimum number of pictures to be taken, it requires more knowledge and time to generate a plan. Probabilistic approaches on the other hand are flexible and adaptive. However, they can only provide probabilistic guarantees for the goal achievement.

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