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Occlusion-aware UAV Path Planning for Reconnaissance and Surveillance in Complex Environments*

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***Abstract*— This paper concerns the reconnaissance and surveillance problem for multi-rotor aerial drones or unmanned aerial vehicles (UAVs) flying over geometrically complex environments, such as mountainous terrains and urban regions. In contrast to the existing literature, our approach takes both UAV kinematics constraints and camera sensing constraints into consideration. We present a two-stage strategy to solve this UAV surveillance problem with the given terrain information. In the first stage, the challenge is to find a set of camera locations called the *vantage waypoint set* to provide full coverage of the area of interest, which can be viewed as a 3D Art Gallery Problem using drones as the observers. In the second stage, one or several UAVs are determined to conduct the full coverage reconnaissance and surveillance duty along individual routes respecting their kinematic constraints in the optimization criterion (the shortest time possible). This variant of the combinatorial traveling salesman problem is solved by introducing unsupervised learning and Bézier curves. The reported results support the feasibility of the proposed solution.**

Index Terms*— *Reconnaissance, occlusion-aware, UAV, path planning, coverage

I. Introduction

Unmanned Aerial Vehicles (UAVs), also known as aerial drones, are becoming increasingly present in our everyday lives [1]. Their extensive use recently jumped from military to hobby and professional applications [2]. They have become the necessary tools for a wide range of activities including but not limited to search and rescue [3], [4], 3D reconstruction [3], delivering goods and merchandise, serving as mobile hot spots for broadband wireless access, and maintaining surveillance and security [5], infrastructure inspection [6], border patrolling [7], etc. [8]. The authors in [3] presented a vision-based autonomy system for UAVs equipped with bioradars that conduct USAR (UAV search and rescue) operations in post-disaster struck environments. Their autonomous navigation and landing system enables the UAV to localize itself, build three-dimensional occupancy maps, plan collision-free trajectories and autonomously explore highly complex unstructured environments while reconstructing a three-dimensional textured mesh of the scene. In general, the coverage problem was first put forward by [9] over a 2D grid environment. One important extension of this problem is for the UAVs, which requires new considerations due to battery life, mobility, and obstacles may cause occlusions. It can be generally classified into two main categories by different UAV motions. Some researchers [10], [11] focus on the deployment of the hovering UAVs to reconnoiter over certain terrains (static coverage). [11] focuses on monitoring every point on the target area while the UAVs keep hovering at certain locations respectively during all the mission time. While the standard static coverage problems typically pay attention to achieve complete/full coverage and track the intruders within it, some interesting research like [12] monitors the routes to access into the target area, which can be seen as an intrusion prevention and detection scheme. Another important problem is the reconnaissance and surveillance problem by moving UAVs (dynamic coverage) [13]–[15]. [15] developed a path planning strategy to maximize the coverage of the area of interest, and track multiple moving ground targets to avoid the surveillance of the UAVs.

In the common reconnaissance and surveillance scenario, the flying UAV equipped with a downward-facing video camera with a certain visibility angle can monitor the targets of interest on the ground, like vehicles, humans, animals, etc. [7], [15], [16]. The surveillance quality can be evaluated in terms of coverage and resolution [17]. As the video camera can only see the points within its cone-shaped field of view (FOV), A *full coverage* requires every point on the target area can be seen at least once in the complete surveillance circle. Rather than ideal flat terrain, in this paper, we concern about a more challenging and realistic variant of this problem that reconnaissance and surveillance in geometrically complex environments, such as mountainous terrains and urban regions. Under this condition, the FOV can be reduced by any kind of obstacles, like mountains, hills, buildings, walls, etc. Furthermore, the lower altitude of the traveling path is preferred for a better resolution of the observed region of the terrain. This problem is likely to become especially significant for the small and micro unmanned aerial vehicles (SUAVs and MAVs). Consequently,

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the optimized path planning for surveillance is indispensable to deliver outstanding performance encountered with the complex environment and limited resources. Although the occlusion-aware UAV path planning is addressed in [18], the resolution requirement is not considered, as all the camera locations are at the same altitude. [19] also assumes that the drones fly on the same height without the influence of the obstacle occlusions. Authors in [20] focus on the problem to cover a 3-D urban structure using a single UAV flying around circular trajectories, however, the trajectory may not be optimal. [21] proposes a probabilistic visibility model to identify near-optimal observation locations for UAV surveillance with both complete and partial occlusions.

In this paper, the author presents an occlusion-aware reconnaissance and surveillance approach to address the aforementioned gaps. We decompose the surveillance problem over geometrically complex environments with varying altitudes and occlusions into a drone version 3D Art Gallery Problem and a variant of the combinatorial traveling salesman problem. A two-stage approach similar to [17], [18], [21], [22] but with a more realistic and efficient solution is proposed. In this first stage, the vantage waypoint set generation, which requires every point on the target area can be seen from at least one position in the vantage waypoint set. Unlike [18], [21], our waypoints to be visited can be at different altitudes. In the second stage, a Self-Organizing Map (SOM) based path planning strategy determines the fast and smooth trajectory along which the vantage waypoint set needs to visit. The trajectory is parameterized as a sequence of Bézier curves, and every point on the target area can be covered at least once in the complete surveillance circle. In contrast to the existing formulation for curvature-constrained vehicles known as the Dubins Traveling Salesman Problem (DTSP) [17], [18], [23] limited by a minimal turning radius or forward velocity, such as fixed-wing UAVs, our planning method is motivated for multi-rotor UAVs that limited by the maximal speed and acceleration.

The remainder of the paper is organized as follows. The addressed problem with the necessary background is formally introduced in the next section. The proposed occlusion-aware surveillance solution is presented in Section III. The computer simulations are performed to validate the performance of the presented approach, and the results can be found in section IV. Section V indicated concluding remarks including future work.

II. Problem Statement

The mathematical description of our multi-rotor drone model at position $c = (x, y, h)$, where $c \in \mathbb{R}^3$ is as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{y} \\ \dot{h} \end{bmatrix} = v \begin{bmatrix} \cos\theta\cos\psi \\ \sin\theta\cos\psi \\ \sin\psi \end{bmatrix} \tag{1}$$

where θ and ψ are the turning angle and the pitch (climb/dive) angle, respectively. The state of our drone is $s = (c, \theta, \psi)$.

The model of the terrain based on several assumptions is described in [11]. The elevation of every point (x_g, y_g) on the terrain can be expressed as $z_g = F(x_g, y_g)$. Let $\mathcal{D}$ be a given subset of the ground $z_g = 0$, which represents an ideal flat ground plane. The objective of our method is to deploy one or several UAVs to reconnoiter the corresponding area of interest

$$\begin{aligned} &\hat{D} := \{(x_g, y_g, z_g)\}, \\ &(x_g, y_g) \in \mathcal{D}. \end{aligned} \tag{2}$$

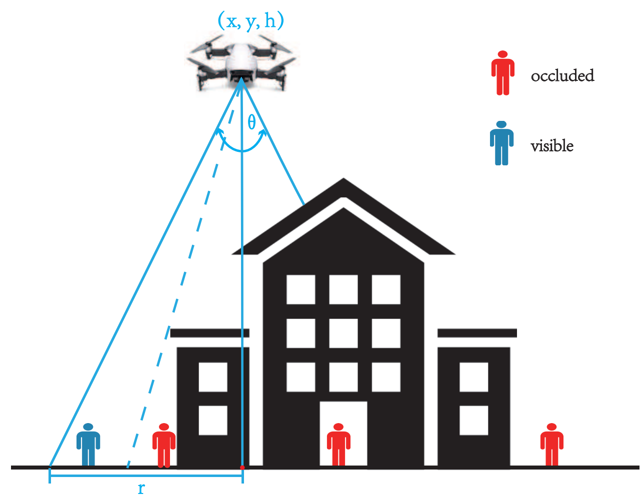


Fig. 1. Occlusion effects on camera sensing

In the addressed reconnaissance and surveillance scenario, our UAV equipped with a downward-facing video camera with a certain visibility angle. It can monitor the relatively small targets of interest on the ground with the required level of details within its FOV. The onboard camera with a given visibility angle $0 < \theta < \pi$ is given in Fig. 1. The drone at (x, y, h) can only see points (x_g, y_g, z_g) of the target area that are inside the cone-shaped field of view (FOV) of radius

$$\begin{aligned} &r(z_g) := (h - z_g) \cdot \tan(\frac{\theta}{2}), \\ &h > z_g. \end{aligned} \tag{3}$$

In the herein addressed reconnaissance and surveillance, we consider one initial waypoint location $p_i \in \mathbb{R}^3$ from vantage waypoint set $P = \{p_1, ..., p_n\}$ where the drone should visit and take video, and the video can be taken within δ distance from p_i, i.e., the video of certain part of the target area can be taken within δ distance from the particular location $p_i \in \mathbb{R}^3$. Thus the vantage waypoint set should contain the waypoint location p_i^* that $||(p_i^*, p_i)|| \leq \delta$.

Under this condition, the problem becomes to find the trajectory to visit δ-neighborhood of all initial waypoint locations, which involves the optimization of the sequence of visits, i.e., a variant of the combinatorial traveling salesman problem. The trajectory is based on the cubic Bézier curve

$$\mathcal{R}(t) = \mathbf{B}_0(1-t)^3 + 3\mathbf{B}_1 t(1-t)^2 + 3\mathbf{B}_2 t^2(1-t) + \mathbf{B}_3 t^3, \tag{4}$$

where $\mathbf{B}_k$ stands for the k-th control point, and $0 \leq t \leq 1$. As the final trajectory $\mathcal{R}$ is closed and smooth curve, which consists of n Bézier curves, any two consecutive curves should be connected at the same endpoint, and the Bézier curves must have the same heading orientation.

Besides, the distance q_{ij} between waypoint p_i and p_j, and the minimum distance q_i between waypoint p_i and the ground should satisfy the following constraints to avoid collisions:

$$q_{ij} \geq c_1 > 2\delta > 0, \quad q_i \geq c_2 > \delta > 0, \tag{5}$$

where c_1 and c_2 are safety margins.

Also, H_{max}, H_{min} are the given maximum and minimum altitudes for the UAVs, the generated vantage waypoint with the following constraints:

$$(x, y) \in \mathcal{D}, h \in [H_{min}, H_{max}]. \tag{6}$$

The *full coverage* of the vantage waypoint set requires (2), (3), (6), and every point on the target area $\hat{D}$ can be seen by one drone at least once in a complete surveillance circle.

Compared with the Dubins model with constant velocity, the multi-motor model can decelerate to make turns and accelerate on fairly straight paths. For the UAV model applied, we prefer the multi-rotor UAV to the curvature-constrained Dubins model. Therefore, the aim is to find the fastest route for the UAV with the maximal vehicle velocity and acceleration limits, rather than the shortest path with Dubins velocity constraints. Therefore, instead of minimizing the length of the trajectory, the expected time to travel the path is considered in this paper.

III. Occlusion-aware Surveillance Algorithm

In this paper, we try to find the vantage waypoint set to fully cover the area of interest first, and then plan a smooth trajectory along with these locations at different altitudes as fast as possible, such that the completion time to visit all the locations is minimal. We propose the following strategy based on a decomposition of the surveillance problem into a variant of the 3D art gallery problem and an instance of the combinatorial traveling salesman problem. It should be noted that our design is not necessarily unique or optimal, but as a preliminary approach is sufficient to prove our point.

A. Stage One: Vantage Waypoint Set Generation

The problem of finding the vantage waypoint set can be viewed as a drone version of the 3D Art Gallery Problem, which has been shown to be NP-hard [24]. The approximation approach is always employed, in this paper, we use a method similar with [11] to estimate the minimal number of the waypoint locations by 3-coloring method [25], and generate the vantage waypoint set $P = \{p_1, ..., p_n\}, p_i \in \mathbb{R}^3$ in two major steps. In the first step, the objective is to determine the 2D coordinates (x_i, y_i) of each vantage waypoints. The second step is to find the best altitudes h_i of sensing with the achieved 2D coordinates (x_i, y_i).

We assumed the terrain $\mathcal{D}$ is a polygon with n vertices, and $\mathcal{D}_1, ..., \mathcal{D}_i$ are obstacles inside $\mathcal{D}$ with $n_1, ..., n_i$ vertices, respectively. Let $\mathcal{E}_1, ..., \mathcal{E}_i$ be inside polygons of $\mathcal{D}_1, ..., \mathcal{D}_i$, respectively. And each $\mathcal{E}_i$ has same number of vertices n_i as $\mathcal{D}_i$. We can consider $\mathcal{E}_i$ as and"top" face, and $\mathcal{D}_i$ as the corresponding "bottom" face of the each obstacle polyhedron model. $\mathcal{A}$ is obtained from $\mathcal{D}$ without $\mathcal{D}_1, ..., \mathcal{D}_i$, which is a non-convex polygon with i "holes". Let $\alpha > 0$ be a constant denoted the relative even area's altitude, and $\alpha + c_2 \leq H_{min}$ holds. And let $\hat{d}_e := \max\left\{d_e, \hat{d}_l\right\}$, d_e is the maximum distance between (x_i, y_i) to the corresponding vertices of $\mathcal{E}_i$, and β is the maximum altitude of the terrain points corresponding to the $\mathcal{E}_i$ and its side quadrilaterals. Let d_l be the maximum length of the triangulation triangles sides whose vertex is one of the two end points. The developed vantage waypoint set generation algorithm can be found in the TABLE I.

B. Stage Two: UAV Path Planning for Surveillance

As mentioned in the previous section, the final trajectory will go through the δ-neighbourhood of each individual vantage waypoint location to reduce the completion time. We do not directly consider the coverage problems introduced by visiting the neighborhoods. This variant of the combinatorial traveling salesman problem is solved by introducing Self-Organizing Map (SOM) and Bézier curves, and the trajectory respecting the kinematic constraints of the UAV.

As we assumed that the UAV will return back to the initial location p_1 after the complete reconnaissance tour, $\delta = 0$ for the initial location. With the vantage waypoint set $P = \{p_1, ..., p_n\}, p_i \in \mathbb{R}^3$ generated above, and the given initial location p_1 and δ, we can determine the final trajectory $\mathcal{R}$ as a sequence $\Sigma = (\sigma_1, \ldots, \sigma_n)$ of Bézier curves $\mathcal{R}_i, 1 \leq i \leq n$. The final trajectory $\mathcal{R} = (\mathcal{R}_{\sigma_1}, \ldots, \mathcal{R}_{\sigma_n}), 1 \leq \sigma_i \leq n$, we need to minimize the estimation of the travel time $\mathbf{E}(\mathcal{R})$, which can be determined from (4). In order to simplify the model, we employ the Model Predictive Controller (MPC) for path following, and the vertical and horizontal movements of the drone are individually considered. we denote a_{ver}, v_{ver}, a_{hor}, v_{hor} as maximal vertical and horizontal accelerations and speeds, respectively. We also assume that the initial and

TABLE I

VANTAGE WAYPOINT SET GENERATION

Algorithm 1 Vantage Waypoint Set Generation

1: **procedure** STEP I
2: Construct polygon $\mathcal{P}$ without "holes" by i non-intersect diagonals with $n+n_1+...+n_i+2i$ vertices
3: Cut $\mathcal{P}$ into triangulation $\mathcal{T}$, whose vertices are $\mathcal{P}$'s, and sides are either $\mathcal{P}$'s or its diagonals.
4: Build the dual graph of $\hat{\mathcal{T}}$ by enlarging $\mathcal{T}$ by the vertices of $\mathcal{E}_i$
5: Paint the vertices of the triangulation $\hat{\mathcal{T}}$ by 3-coloring method in [25]
6: The minimum number of vertices subset of the three is selected as the 2D coordinates (x_i, y_i) of the vantage waypoint set
7: **end procedure**
8: **procedure** STEP II
9: **while** $h \leq Z_{min}$ **do**
10: **if** (x_i, y_i) is not a vertex of any polygons $\mathcal{E}_i, \mathcal{D}_i$ **then** $h_i := \max\left\{Z_{\min}, \alpha + \frac{d_l}{\tan(\frac{\theta}{2})}\right\}$
11: **else if** (x_i, y_i) is a vertex of some polygons $\mathcal{E}_i, \mathcal{D}_i$ **then** $h_i := \max\left\{Z_{\min}, \beta + c_2 + \frac{\hat{d}_e}{\tan(\frac{\theta}{2})}\right\}$
12: **else** $h_i := \max\left\{Z_{\min}, a + c_2 + \frac{\hat{d}_l}{\tan(\frac{\theta}{2})}\right\}$
13: **end if**
14: **end while**
15: **end procedure**
16: **return** vantage waypoint set $P = \{p_1, ..., p_n\}, p_i = (x_i, y_i, h_i)$

final velocity of the drone is zero, so that the drone will start from the initial location p_1 with zero velocity and return back to it in the end. The estimation of the travel time $\mathbf{E}(\mathcal{R})$ and the profile of the velocity can be computed by the method in [26] by maximum possible tangent acceleration $a_{tan} = \sqrt{a_{hor}^2 - a_{rad}^2}$, a_{rad} is the radial acceleration.

The adaptation can be considered as a movement of the waypoint locations towards the alternate location s_p and a new location of each adapted waypoint location ν becomes ν' and it follows the standard SOM learning [27].

$$\nu' = \nu + \mu f(\sigma, d)\,(s_p - \nu) \tag{7}$$

where μ is the learning rate, σ is the learning gain, d is the distance of ν from the winner waypoint location ν^*, and $f(\sigma, d)$ is the neighbouring function

$$f(\sigma, d) = \begin{cases} e^{\frac{-d^2}{\sigma^2}} & \text{for } d < 0.2M \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

where M is the current number of waypoints.

The surveillance planning algorithm will stop the adaption if $i \leq i_{max}$ or ν^* are negligibly close to their respective s_p, or all winner waypoint locations are inside the δ-neighborhood of the respective initial waypoint location. Otherwise, go to Step 3. An intersection of the straight line segment (s_p, p) with the sphere in $\mathbb{R}^3$ shaped δ-neighborhood of p is used

TABLE II

UAV PATH PLANNING ALGORITHM

Algorithm 2 UAV Path Planning Algorithm

1: Create the loop $\mathcal{N}$ with n waypoint locations around the initial location p_1
2: Set the learning gain $\gamma = 12.41n + 0.6$, the learning rate $\mu = 0.5$, and the gain decreasing rate $\eta = 0.1$. Set the epoch counter $i = 1$, $i_{max} = 100$.
3: **while** the termination condition hasn't been reached **do**
4: **for** $p \in \Pi(P)$ **do**
5: **for** each learning epoch **do**
6: determine ν^* and s_p
7: Adapt ν^* and its neighbours towards s_p using (7)
8: remove all non-winner waypoint locations and perform LIO-based optimization of the trajectory
9: Update learning parameters: $\gamma = (1-\eta)\gamma, i = i+1$
10: **end for**
11: **end for**
12: **end while**
13: **return** final trajectory $\mathcal{R}$

to determine the alternate location s_p towards which the network is adapted instead of p to save the travel time.

IV. RESULTS

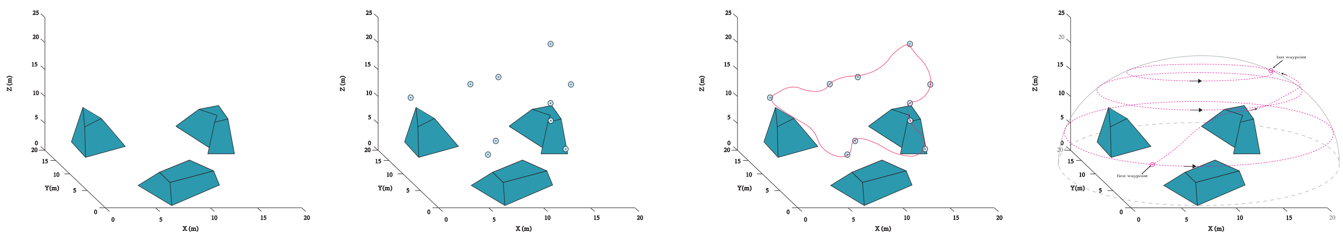
To validate the effectiveness of the proposed algorithm, two simulation scenarios are carried out in this section. The 20m by 20m terrain of the target area with $i = 3$ random shaped obstacles are shown in Fig. 2(a), and the obstacles have $n_1 = 3, n_2 = 4, n_3 = 4$ vertices, respectively. The simulation is conducted with the following parameters in the TABLE III.

A. Single-Area Single UAV

To confirm the performance of our surveillance strategy in a complex environment, we carry out verification in the following scenario. We use the drone version 3D Art Gallery Theorem [11] to obtain the vantage waypoint set, and the δ-neighborhood of all 10 waypoint locations at different altitudes from 6.4m to 23.3m are shown in Fig. 2(b). The final surveillance path with Bézier curves by the proposed algorithm in Fig. 2(c) took 53s. The time-optimal surveillance path planning algorithm in [20] was then run on the same environment in Fig. 2(d). Under the same forward velocity v_f, vertical velocity v_z, and vertical acceleration a_z as our proposed method, the generated trajectory took 147.6s to finish the surveillance duty. Clearly, the proposed method out-performed the compared algorithm on both traveling time and trajectory length. As the compared method does not directly take the problems caused by occlusions into consideration, we may need to apply geometric computation to calculate the uncovered part and deploy other drones for complete coverage.

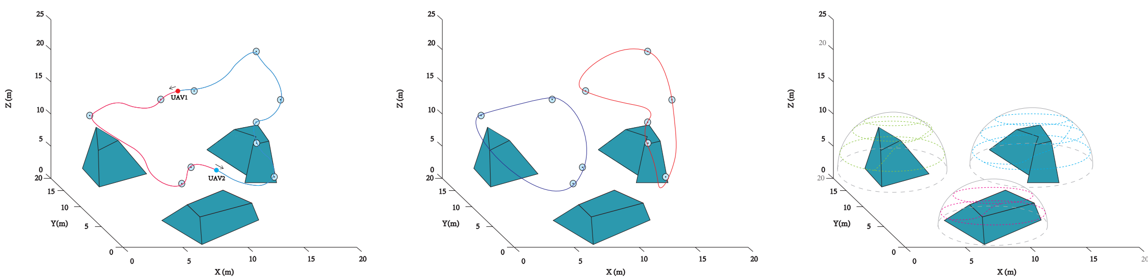
TABLE III
SIMULATION PARAMETERS

camera					**mobility of UAV for proposed method**				**mobility of UAV for time-optimal method**		
θ	H_{min}	c_1	c_2	α	a_{ver}	a_{hor}	v_{ver}	v_{hor}	a_z	v_z	v_f
$\frac{\pi}{2}$	4m	1m	0.5m	0.2m	$0.5m/s^2$	$1.2m/s^2$	$0.5m/s$	$1.2m/s$	$0.5m/s^2$	$0.5m/s$	$1.2m/s$



(a) Model of the target area
(b) Vantage waypoint set
(c) Proposed UAV path
(d) Time-optimal UAV path with hemispherical coverage model

Fig. 2. UAV surveillance trajectory using (a)-(c) proposed strategy and (d) time-optimal strategy in [20] - Single UAV



(a) Two UAVs share one path, the red/blue point is its initial position
(b) Two UAV, two paths
(c) Three UAV, three paths

Fig. 3. UAV surveillance trajectories using (a)-(b) proposed strategy and (c) time-optimal strategy in [20] - Multiple UAVs

B. Single-Area Multiple UAVs

In this scenario, multiple UAVs are applied to conduct the full coverage reconnaissance and surveillance duty. The same waypoint locations are shown in Fig. 2(b). As shown in Fig. 3(a), two drones in different initial locations are sharing the same path. Fig. 3(b) is the condition that each UAV has an individual trajectory to cover only part of the terrain. In addition, the coverage of the area of interest is achieved when both of them finish their surveillance circle. Both scenarios apparently increase the duration to cover the area of interest, so that the average time to cover any arbitrary point between two consecutive times is decreased around 47%. In other words, the points of interest are monitored more frequently. We also deploy three UAVs to cover each individual obstacle as a comparison. However, the uncovered part due to the overlapping of the flight surfaces is inevitable.

V. CONCLUSION

In this paper, we consider the reconnaissance and surveillance problem for unmanned aerial vehicles (UAVs) flying over geometrically complex environments, such as mountainous terrains and urban regions. The main contribution of this paper is to develop an occlusion-aware UAV surveillance strategy regarding the kinematic constraints of the UAV and the obstacles' occlusions. The UAV will visit a certain vantage waypoint set as fast as possible and ensure that any point in the area is seen from some position. The simulation result demonstrated the validation of the algorithm. The problem of finding the vantage waypoint set can be viewed as a drone version of the 3D Art Gallery Problem. The unsupervised learning and Bézier curves are used to generate a smooth and fast trajectory for the drone. One interesting direction for future research is to take the realistic pan-tilt capability of the onboard camera into consideration. In other words, adding the flexibility in the camera's orientation [28]. Another important direction for future research is to extend the obtained results to the case on a team consisting of groups of drones, so-called the problem of navigation for sweep coverage in cluttered environments [29].

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