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Moving ground target tracking in dense obstacle areas using UAVs

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Abstract: Tracking moving ground targets using unmanned air vehicles (UAVs) has important applications in several areas. Keeping a close line of sight from a UAV to a target in a densely populated area is a challenging task because of many constraints. An algorithm for several UAVs to track a moving target cooperatively is proposed. From random samples on the ground and obstacles, a cost inversely proportional to chance to keep the target inside the camera field of view is defined. The centre of the flight path and the separation angles between UAVs along the circular flight path is optimally determined to minimise the cost. The efficiency of the algorithm is tested by Monte-Carlo simulations based on random scenario generators.

Keywords: Aircraft Control; Path Planning; Target Tracking.

1. INTRODUCTION

Tracking moving ground targets using a camera mounted on unmanned air vehicles (UAVs) has important applications in military and civilian purposes. Many results related to this topic have been presented in the last few years. Most of them are related to identification and classification of multiple targets or estimation of certain states using various sensors including a vision sensor such as a camera and a moving indication sensor [Schmitt et al., 2002, Hwang et al., 2004, Hong et al., 2004, Chitrakaran et al., 2005, Aguiar and Hespanha, 2006]. In Kanchanavally et al. [2004], the prediction and search algorithm was presented for several UAVs cooperatively tracking a moving target, accounting for the time delay between the time when the information arrived and the time when a UAV arrived on the target to do some operations. Martínez and Bullo [2006] presented an optimal sensor placement and motion coordination algorithm for a set of mobile robots to track a target.

In this paper, we consider a novel target tracking scheme for UAVs. Our focus here is to find optimal flight paths for UAVs to minimize the chance of losing the moving target under mild assumptions. Multi-UAV target tracking is in spirit the same as multi-sensor target tracking which already has been a popular topic in the literature, e.g. Smith and Singh [2006], and studied in many directions. These directions include decentralized estimation of the target location [Speranzon et al., 2006], target tracking under communication constraints [Zengin and Dogan, 2005], fault-tolerant cooperative target tracking [Kim et al., 2008], and so on. However, we note that all these considerations are mainly focused on signal processing or data fusion issues, assuming that UAVs follow pre-determined but target-dependent flying routes. In contrast, our interest in this paper is to *design* the UAVs flying paths such that the probability that the tracked target is within the line of sight of at least one UAV is maximized.

Unfortunately, we note that there are only a handful of studies in the literature pursuing our interested direction. In particular, we mention the works of Peot et al. [2005] and Rafi et al. [2006]. In Peot et al. [2005], the authors consider an optimal path planning strategy for visiting a series of static targets in urban domains. When a UAV or UAVs approach each target, several practical sensing issues were considered (e.g. line of sight, desired dwell, desired point of view) using a software package (Design Sheet). Although the considered problem is similar to our interest, this work is mainly for static target tracking. In contrast, a circular pattern navigation algorithm for autonomous target tracking has been studied [Rafi et al., 2006, Wise and Rysdyk, 2006, Kim and Sugie, 2007]. Rafi et al. [2006] presented an algorithm that essentially controls turn rate for a UAV and camera angles for the associated gimbal, and the performance is supported by numerical simulations. However, one missing part, as far as our interest is concerned, is that there are no physical obstacles which hinder UAVs from tracking a target.

Our present work may be considered as a combination of the aforementioned two works. Inspired by Rafi et al. [2006], we control two parameters: the pivot point (r_c) around which UAVs follow a circular pattern and the spacing (Φ) between the UAVs, so that the utility of the sensing actions by the UAVs is maximized as in Peot et al. [2005]. In the next section, we clearly define the problem considered in this paper and pose it as an optimization problem. Then, an approximating scheme follows to handle the original problem in real-time. The approximation is

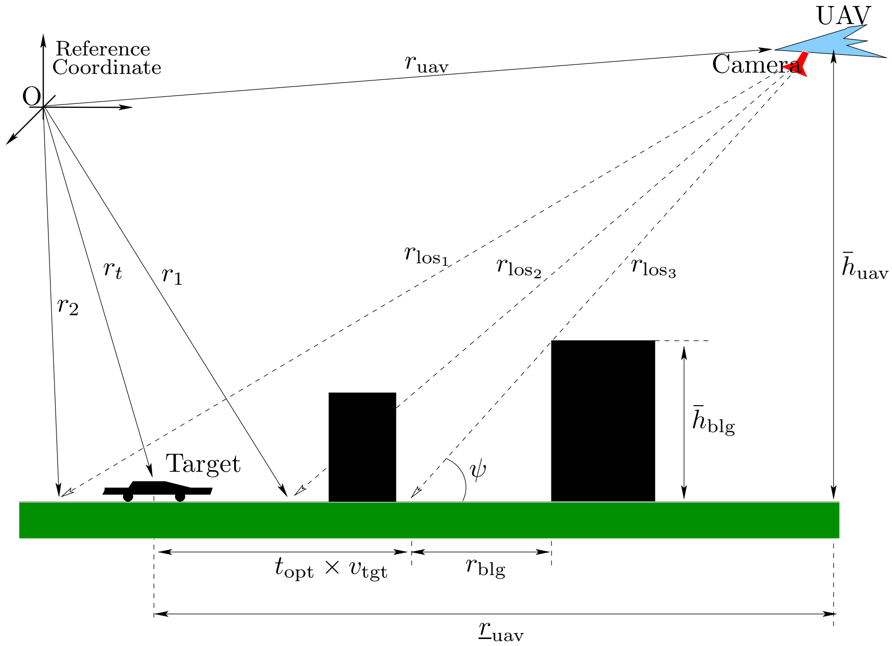

Fig. 1. Moving ground target tracking using UAV camera. The main objective is of keeping the target inside the camera field of views.

(a) 3D-View (b) 2D-View

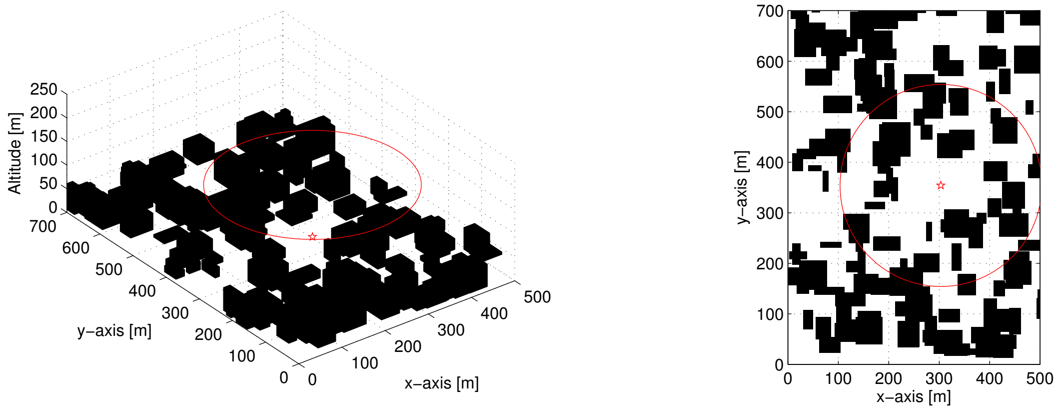

Fig. 2. Target is indicated as a star and buildings are represented by boxes in black. The red circle is the flight path with the allowed maximum altitude and minimum turn radius.

motivated from Kim and Hespanha [2003] where randomisation sampling was used for reducing the computational cost for solving the anisotropic shortest path problem. Finally, the performance of algorithm is demonstrated via extensive numerical simulations.

2. PATH PLANNING FOR TARGET TRACKING

In this section, the optimisation problem for optimal UAV path planning to track a moving ground target is formulated and an efficient approximation method to solve the nonlinear programming using a random sampling approach is presented.

2.1 Optimisation Problem Formulation

Assume that the aircraft is a fixed wing type. Hovering is not possible and the speed is maintained as a constant. In addition, it is assumed that the geographical information including locations and shapes of ground obstacles such as buildings and geographical altitude distributions are available. This is not very restricted assumption because usually most major geographical obstacles over the operational regions are already in the database. It is also assumed that the camera mounted on the UAV, which is used for tracking a moving ground target, scans the region fast enough and the field of view is wide enough so that its dynamics and relative attitude can be ignored. That is, the time interval that the camera scans r_{los_i} in Figure 1 is relatively short compared to the distance that aircraft flies during the interval. Hence, the only factor for target tracking is the relative location of aircraft from the target and the obstacles.

Consider the case that the altitude of the UAV is relatively lower, or closer, to the average height of buildings. In other words, the area could be extremely dense by high-rise buildings and/or hills, etc. Figure 2 shows an example map, where the black boxes are the buildings on the ground and the location of target to be tracked is indicated by the red star. The red circle represents the flight path of UAV with the minimum turn radius and the maximum allowed altitude. If the maximum allowed altitude for the UAV is restricted to be relatively close to the maximum height of ground obstacles, then the line of sight from the aircraft to the moving ground target could be blocked frequently by the obstacles. Hence, the flight path has to be designed to minimise the blocking time so that the chance to miss the target is minimised. For one UAV, the optimal path could be given as a circular path centred at the current position of the moving target with its maximum altitude and minimum turn radius as shown in Figure 2. With this path, the angle from aircraft to a target could be maximised so that the chance to be blocked by any obstacles becomes less. However, actual situations are more complicated because the ground obstacles are highly irregular and/or asymmetric.

Let t_{opt} be the time consumption that an optimisation algorithm, which minimises the chance that the line of sights are blocked, is solved on-board the aircraft or is solved at a commanding centre and the solution is received via communication. For a given maximum speed of the ground target, v_{tgt}, then the radius of region where the target is included is given by $t_{\text{opt}} \times v_{\text{tgt}}$ shown in Figure 1. For example, if the maximum allowed algorithm time consumption is limited to 5s and the maximum target velocity is 72 km/h, then the radius is given by 100 m. The smaller circle indicated by thicker line in Figure 3 is shown the possible region where the target is located after 5s. Define this candidate region that includes the target as follows:

$$\mathcal{S}_{\text{tgt}} := \{r|\ \|r_t - r\| < t_{\text{opt}} \times v_{\text{tgt}} \text{ and } r \text{ is not overlapped with any buildings.}\} \quad (1)$$

where r is the location vector in $\mathcal{R}$, $\mathcal{R}$ is the geographical area, r_t is the target location vector in $\mathcal{R}$ and $\|\cdot\|$ is the euclidean norm. Three arrows shown in Figure 3 are the line of sight vector examples from the UAV to an arbitrary point inside the region of interest, $\mathcal{S}_{\text{tgt}}$. Two broken arrows are blocked by some buildings and one normal arrow indicates that the region pointed by the arrow is covered by the camera mounted on the aircraft. The area observed by the camera at a specific location of aircraft, r_{uav}, will be defined as follows:

$$\mathcal{S}_{\text{obs}}(r_{\text{uav}}) := \{r|\ r_{\text{los}} \text{ is not blocked by any obstacles.}\} \quad (2)$$

where $\mathcal{S}_{\text{obs}}(\cdot) \subset \mathcal{S}_{\text{tgt}}$, r_{los} is the line of sight vector, which is defined by $r_{\text{los}} := r - r_{\text{uav}}$ and r_{uav} is the location of aircraft (See Figure 1).

To maximise the chance to observe the ground target for a UAV, the optimisation problem can be formulated as follows:

$$\max_{r_c} J = \max_{r_c} \int_{r_{\text{uav}}} Ar(r_1, r_2)\, dr_{\text{uav}} \quad (3)$$

where r_1 is the element of $\mathcal{S}_{\text{obs}}$, r_2 is the element of $\mathcal{S}_{\text{tgt}}$ and $Ar(\cdot,\cdot)$ is the weighted area function, which is defined as follows:

$$Ar(r_1, r_2) = \int_{\mathcal{S}_{\text{tgt}}} p_{\text{tgt}}(r_1)\mathcal{I}(r_1, r_2) d\mathcal{S}_{\text{tgt}}, \quad (4)$$

$p_{\text{tgt}}(r_1)$ is the probability density function of the target location at r_1 during the time, $t \in [t_c, t_c + t_{\text{opt}}]$, t_c is the current time and $\mathcal{I}(r_1, r_2)$ is an indicator function such that

$$\mathcal{I}(r_1, r_2) = \begin{cases} 1, & \text{for } r_1 \text{ and } r_2 \text{ are in } \mathcal{S}_{\text{obs}} \cap \mathcal{S}_{\text{tgt}} \\ 0, & \text{otherwise} \end{cases}, \quad (5)$$

Since the aircraft is assumed to be flying along a circular orbit whose centre is r_c and the radius corresponds to the minimum turn radius of the aircraft, $\underline{r}_{\text{uav}}$, the location of aircraft is given by $r_{\text{uav}} = \underline{r}_{\text{uav}}\theta$, where θ is in $[0, 2\pi]$. Once the centre is determined, then the location of aircraft is a function of the angle on the orbit. Hence, the cost function can be written as

$$\max_{r_c} J = \max_{r_c} \int_0^{2\pi} Ar(r_1, r_2)\, \underline{r}_{\text{uav}}\, d\theta \quad (6)$$

The optimisation problem is maximising the observed area weighted by the target probability density. In addition, for the case that more than one aircraft is available, another control variable is introduced that gives the optimal formation of the aircraft. For example, if two aircraft are assigned to track one target, then they will fly along the same orbit but with different locations, i.e., they will fly with some fixed separation angle, ϕ. For multiple aircraft, the cost function is given by

$$\max_{r_c,\Phi} J = \max_{r_c,\Phi} \int_0^{2\pi} Ar(r_1, r_2)\, \underline{r}_{\text{uav}}\, d\theta \quad (7)$$

where $\Phi := \{\phi_1, \phi_2, \ldots, \phi_{n_{\text{uav}}-1}\}$, ϕ_i is the separation angle between the i-th and $(i+1)$-th aircraft, r_1 is the element of the following set, $\mathcal{S}_1$:

$$\mathcal{S}_1 = \bigcup_{i \in I} \mathcal{S}_{\text{obs}}\left(r^i_{\text{uav}}\right), \quad (8)$$

$\mathcal{S}_{\text{obs}}$ in the indicator function, (5), is replaced by $\mathcal{S}_1$, $I = \{1, 2, \ldots, n_{\text{uav}}\}$ and n_{uav} is the number of aircraft.

Equivalently, the above maximisation problem is re-posed as a minimisation problem as follows:

$$\min_{r_c,\Phi} J = \min_{r_c,\Phi} \int_0^{2\pi} \bar{A}r(r_1, r_2)\, \underline{r}_{\text{uav}}\, d\theta \quad (9)$$

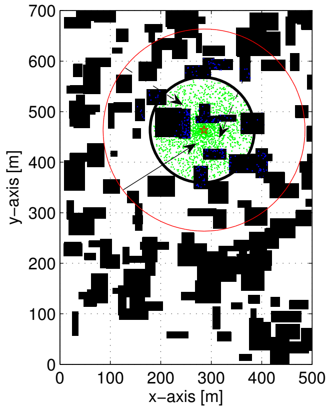

Fig. 3. The target is possibly inside the smaller circle and the larger circle is a possible flight path of UAV. Random samples on the region of interest are indicated by dots located on either the ground or the top of buildings. The line of sight from a UAV is defined by the line from a point on the larger circle to each dot on the ground.

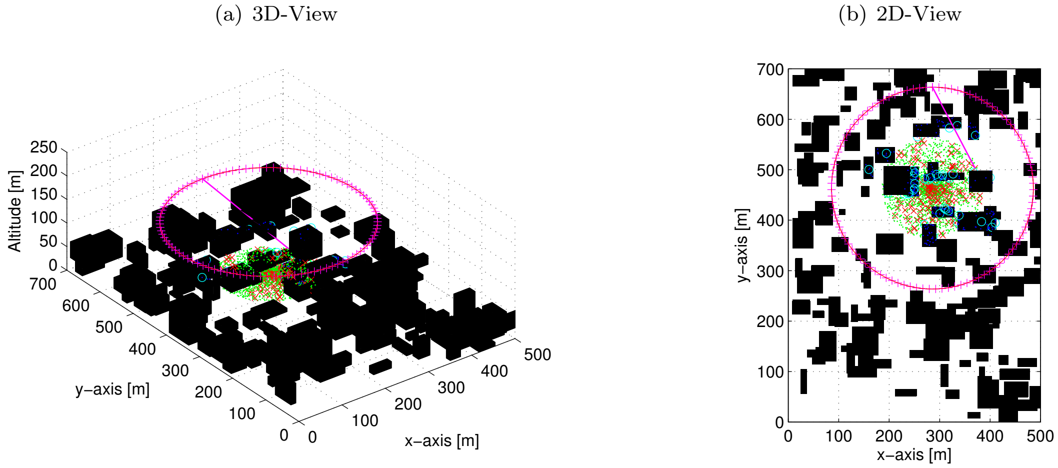

Fig. 4. Since the calculation amount increases fast as the number of samples increases, the smaller samples, indicated by cross and circle, are chosen randomly from the original larger samples for each way point of flight path.

where $\bar{A}r(r_1, r_2)$ is defined the exactly same as $Ar(r_1, r_2)$ except that $\mathcal{S}_{\rm obs}$ in the indicator function is replaced by the following, $\mathcal{S}_1$:

$$\mathcal{S}_1 = \left[\bigcup_{i=I} \mathcal{S}_{\rm obs}\left(r^i_{\rm uav}\right) \right]^c, \tag{10}$$

$[\ldots]^c$ is the complement set relative to $\mathcal{S}_{\rm tgt}$, i.e., $\mathcal{S}_{\rm tgt} - [\ldots]$. Since the constraints given by the obstacles are, in general, non-convex and the time allowed to solve the problem is of a few seconds range, the exact solution of the optimisation problem above is not feasible. In the next section, this minimisation problem is approximated so that it can be solved in a matter of few seconds.

2.2 Approximate Optimisation Problem

As a first stage of the simplification of the optimisation problem, (9) is to be solved in two steps as follows:

(1) find the optimal r_c for one UAV
(2) find the optimal Φ for n_A UAVs for the r_c determined in the previous step

For step-(1), to approximate the original minimisation problem, (9), discretise the flight path and the cost function as approximated by

$$\min_{r_c} J \approx \min_{r_c} \sum_{k=1}^{n_\theta} \bar{A}r\left(r_1, r_2\right) \; \frac{2\pi \underline{r}_{\rm uav}}{n_\theta} \tag{11}$$

where n_θ is the number of segments along the flight path and the example is indicated in Figure 4 by a plus (+) symbol along the circular path. Note that r_1 is a function of the UAV location and

$$\bar{A}r(r_1, r_2) = \int_{\mathcal{S}_{\rm tgt}} p_{\rm tgt}(r_1) \mathcal{I}(r_1, r_2) d\mathcal{S}_{\rm tgt} \tag{12}$$

Since this is the case for one UAV, the indicator function is given by

$$\mathcal{I}(r_1, r_2) = \begin{cases} 1, & \text{for } r_1, r_2 \in \mathcal{S}^c_{\rm obs} \cap \mathcal{S}_{\rm tgt} \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

Assume that $p_{\rm tgt}$ follows the typical shapes such that one peak exists around the current position. To efficiently evaluate the integral, (12), n_g-number of random samples are extracted from $\mathcal{S}_{\rm tgt}$. Define the set N_g as follows:

$$\begin{aligned} N_g := \{ & r_i \text{ for } i = 1, 2, \ldots, n_g |\; r_i \in \mathcal{S}_{\rm tgt}, \text{ where} \\ & r_i = r^i_g \left(\cos\theta^i_g, \sin\theta^i_g\right), r^i_g \sim U(0, r_{\rm tgt}), \theta^i_g \sim U(0, 2\pi) \;\} \end{aligned} \tag{14}$$

where for all r_i the altitude is assumed to be constant (but it is easy to extend for non-flat ground cases) and $U(a, b)$ is a uniformly distributed random number between a and b. By sampling uniformly in the radius and the angle direction, the resulting samples are concentrated more around the current centre. In Figure 3, they are indicated by dots inside the smaller circle white region. Similarly, n_b-number of random samples, which are uniformly distributed on the top surface of obstacles, where the obstacles are in the following set:

$$\mathcal{S}_{\rm blg} := \{r |\; \|r_t - r\| < t_{\rm opt} \times v_{\rm tgt} + r_{\rm blg}\} \tag{15}$$

where $r_{\rm blg}$ is given by

$$r_{\rm blg} = \bar{h}_{\rm blg} / \tan\psi = \bar{h}_{\rm blg}\left(\underline{r}_{\rm uav} - r_{\rm tgt}\right) / \bar{h}_{\rm uav} \tag{16}$$

ψ is shown in Figure 1, $\bar{h}_{\rm blg}$ is the maximum height of the ground obstacles, $\bar{h}_{\rm uav}$ is the maximum allowed altitude of aircraft and $r_{\rm blg}$ is the maximum distance from $r_{\rm tgt}$ toward the outside of $\mathcal{S}_{\rm tgt}$ where the line of sight could be blocked by an obstacle (See Figure 1). Define the set N_b as follows:

$$\begin{aligned} N_b := \{ & r_i \text{ for } i = 1, 2, \ldots, n_b |\; r_i \in \mathcal{S}_{\rm blg}, \text{ where} \\ & r_i = r^i_b \left(\cos\theta^i_b, \sin\theta^i_b\right), r^i_b \sim U(0, r_{\rm tgt}), \theta^i_b \sim U(0, 2\pi) \;\} \end{aligned} \tag{17}$$

Since r_i in N_g are more concentrated on the centre, and the obstacles closer to the centre have more possibility to block some line of sight vectors, the samples in N_b are distributed more closer to the centre. This set is shown in Figure 3 by the dots on the top of obstacles indicated by filled-squares around $\mathcal{S}_{\rm tgt}$ set.

Whether a line of sight vector from $r_i \in N_g$ to a fixed $r_{\rm uav}$ on the circular flight path is blocked by obstacles, $r_j \in N_b$, or not can be checked by the relative distances and attitudes between two line of sight vectors, $r_i \in N_g$ and $r_j \in N_b$ to the aircraft. Then, the integral, (12), can be approximated by

$$\bar{A}r(r_1, r_2) \approx (\#\text{ of samples that are blocked among } n_g)/n_g \tag{18}$$

Since n_g and n_b have to be greater than certain numbers to keep approximation errors less than some levels, the

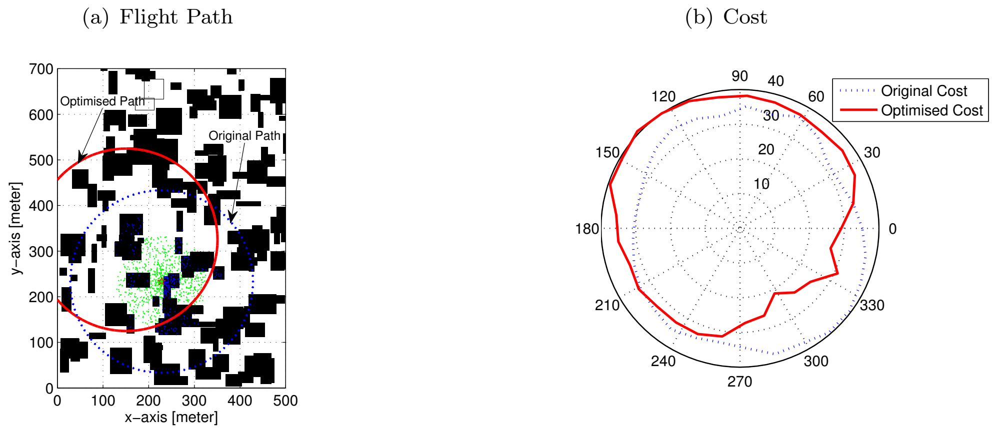

Fig. 5. Flight path with optimal centre is depicted by the red solid circle.

number of combinations to be checked, $n_g \times n_b$, increases quickly to the level where the computation cost is too high as n_g and/or n_b increases. To avoid this difficulty, random re-samples, whose numbers are much smaller than n_g and n_b, are taken from N_g and N_b, i.e. $\tilde{n}_g \ll n_g$ and $\tilde{n}_b \ll n_b$, where $\tilde{n}_g$ and $\tilde{n}_b$ are the number of re-samples from the set N_g and N_b, respectively. This re-sample procedure is repeated for each k from 1 to n_θ along the flight path. Then, for each k, the approximated integral is given by

$$\bar{A}r(r_1, r_2) \approx (\text{\# of samples that are blocked among } \tilde{n}_g)/\tilde{n}_g \quad (19)$$

The re-sampling example is shown in Figure 4, where the re-sampling points from N_g and N_b are indicated in red-cross and blue-circle, respectively.

To obtain r_c to minimise the cost, (11), the following observation is used: to maximise the area monitored by the UAVs, flight path should be as close as possible to the densely populated region so that the line of sight angle is maximised. To do this, the line search is performed along the direction where the term inside the summation in (11) is maximum among $k = 1, 2, \ldots, n_\theta$. The moving direction of the centre is decided so that the cost decreases. Then, the centre of the flight path, r_c, is moving away with a constant distance step until the cost is not improved as follows:

$$r_c^{\text{new}} = r_c^{\text{old}} + \text{sign}(\Delta J)\ \Delta r\ e_{\text{worst}} \quad (20)$$

where sign$(\cdot)$ is the sign function, which returns -1, 0, or 1, depending on the sign of argument, $\Delta J = J_{\text{new}} - J_{\text{old}}$, sign$(\Delta J)$ equals to -1 at the initial, Δr is the step size, and e_{worst} is the unit direction vector pointing the maximum cost when the centre of flight path is equal to the current target position. As a result, the centre moves away from the worst direction when the cost is improved and it moves back toward the worst direction when the cost increases. A calculation example is shown in Figure 5. The original path and the cost shape along the flight path are shown in the blue dotted lines and the corresponding optimised ones are shown in the red solid lines.

For the algorithm step-(2), which is for finding optimal separation angles between multiple UAVs, observe that the approximated weighted area function, (19), which is optimised by adjusting the centre of flight path at the step-(1), is an implicit function of angle, indicating the location of the UAV on the circular flight path. Moreover, it has a period of 2π, i.e.

$$\bar{A}r[r_1(\theta), r_2] = \bar{A}r[r_1(\theta + 2\pi), r_2] \quad (21)$$

where θ is the angle indicating the position of the UAV on the flight path. Consider the case that two UAVs are available. Then, two area functions are given by $\bar{A}r(\theta)$ and $\bar{A}r(\theta+\phi)$, where the notational simplicity $\bar{A}r$ is written as a function of θ directly, and ϕ is the separation angle of the second UAV from the first UAV. Then the optimisation is given by

$$\min_{\phi\in[0,2\pi)} J = \min_{\phi\in[0,2\pi)} \int_0^{2\pi} \min\left[\bar{A}r(\theta), \bar{A}r(\theta+\phi)\right] d\theta \quad (22)$$

where the min-function inside the integral counts the fact that whenever the target area is observable from at least one of the UAV's camera, the tracking mission is satisfied. The integral in this case has to be approximated by discretising the integration interval so that the calculation amount is not increasing too much as follows:

$$\min_{\phi\in[0,2\pi)} J = \min_{\phi\in[0,2\pi)} \sum_{k=1}^{\tilde{n}_\theta} \min\left[\bar{A}r(\theta), \bar{A}r\left(\theta + k\frac{2\pi}{\tilde{n}_\theta}\right)\right] \frac{2\pi}{\tilde{n}_\theta} \quad (23)$$

where $\tilde{n}_\theta$ is the number of samples that is less than n_θ. This can be easily extended for multiple-UAV cases whose number is more than two. In the next section, the performance of algorithm is demonstrated for some random maps.

3. MONTE-CARLO SIMULATION

The update algorithm for the flight path centre, (20), is tested by 1000-random scenarios. The mean values of the cost, (11), for the original path and the optimised path are 13,470 and 12,974, respectively. The cost is improved about 3.68%. Average calculation time is about 2.57s with the standard deviation 1.43, the maximum 9.73s and the minimum 0.67s. This clearly demonstrates the possibility of real-time application of the suggested algorithm. The optimal path for two UAVs is obtained by solving (23) and shown in Figure 6. The separation angle is about 100° and the final cost is reduced significantly compared to the other two costs. All calculations were performed on a 3.06 GHz Pentium IV machine with 1.00 GB of RAM using Windows XP Professional, MATLAB 7.4.

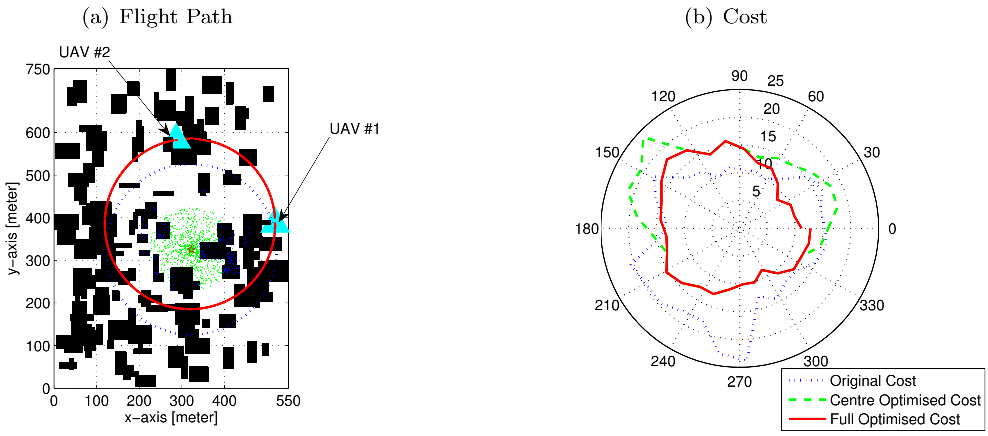

Fig. 6. Flight path with optimal centre for two UAVs is depicted by the red solid circle. Two UAVs separation angle is about 100°.

4. CONCLUSION AND FUTURE WORK

An efficient algorithm for tracking a moving target using a group of UAVs is developed. The computation complexity is overcome using a randomisation sampling method. Random samples are taken from the ground and obstacles in the region of interest and a cost counting the chance to keep the target inside the camera field of view is defined. The centre of the flight path and the separation angles between UAVs are optimally determined by minimising the cost. The efficiency of the algorithm is tested by Monte-Carlo simulations based on random scenario generators. As for future research directions, currently we are studying flight path shapes other than circular and aiming to include the shape as an optimisation parameter and considering terrain altitudes information for constructing the cost.

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