Optik 123 (2012) 2226–2229

Contents lists available at SciVerse ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

A restricted-direction target search approach based on coupled routing and optical sensor tasking optimization

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ARTICLE INFO

Article history:
Received 5 June 2011
Accepted 15 October 2011

Keywords:
Restricted-direction target search
Unmanned Air Vehicle (UAV)
Optical sensor

ABSTRACT

A key issue in UAVs (Unmanned Air Vehicles) and UAV-mounted sensor control is the target search problem: finding targets in minimum time. In this paper, we proposed a restricted-direction target search approach based on coupled routing and optical sensor tasking optimization. In this method, we consider a single UAV, which is equipped with two optical sensors to view a limited large region of the dynamic environment. The UAV moves in the dynamic environment, searches for targets of interest, and is capable of avoiding obstacles and threats immediately. The paths are obtained considering actual maneuverability limitations of the UAV and are evaluated according to optimization of the optical sensor tasks for the duration of the path. Series of comparative experimental results demonstrate that this algorithm makes effective use of the coupled method of optimization and performs significantly better than previously proposed approaches.

1. Introduction

Search theory, as we know it today, began with work by Koopman [1], Stone [2] and others. The work was initially motivated by the desire to develop efficient search methods to find enemy marine vessels. Agencies such as the US Coast Guard have applied search theory to search and rescue missions with great success, measured in saved lives [3]. Other search applications include exploration and surveillance [4].

Early search theory focused on the allocation of search effort to areas within the search region, as finding optimal search paths on these areas is intuitive or searcher motion is unconstrained. If this is not the case, we are presented with a more difficult problem of finding optimal paths for the searchers. There are some studies of the search problem as an optimal control problem in continuous time and space [5], but these generally apply to a very restrictive set of initial target distributions. A more practical approach is to discretize the search space and formulate the search problem on a graph. Then the search path describes a sequence of regions to search along with an amount of time that should be spent in each region. Although this discretization simplifies the problem to some extent, it is still computationally very difficult. Trummel and Weisinger [6] showed that the single-agent search problem is NP-Hard even for a stationary target. Eagle, Yee and Stewart formulated the moving target problem as a nonlinear integer program and proposed branch and bound algorithms to solve it. This provided a significant computational reduction over a total enumeration, but the problem still has exponential complexity [7,8]. DasGupta et al. [9] presented an approximate solution for the stationary target search based on an aggregation of the search space using a graph partition. Chen and Chang [10] proposed an agent-based simulation for multi-UAVs coordinative sensing. Collins et al. [4] proposed a graph-based approximation algorithm for cooperative routing problems and achieved great success.

This paper addresses the search problem in which a single UAV is searching for one or more targets in a bounded geographic environment, with the objective of locating targets of interest in minimum time and avoiding obstacles and threats. The UAV is equipped with two gimbaled optical sensors that can be steered to view a limited region of the environment it is visiting, known as field of view (FOV). As the FOV moves on the ground and takes measurement, it will gather information about the environment in the form of automatic target recognition (ATR) data and determine whether the target is located in a specific region or not. Besides, the UAV is assumed to have some maneuverability limitations, which constrain the maximum turning radius.

Another important aspect of the search problem is control of the optical sensor. As the sensors mounted onboard UAVs have become more sophisticated and dynamically controllable, enabling the sensing neighborhood to be steered about the UAV platform, the

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0030-4026/$ – see front matter
doi:10.1016/j.ijleo.2011.11.018

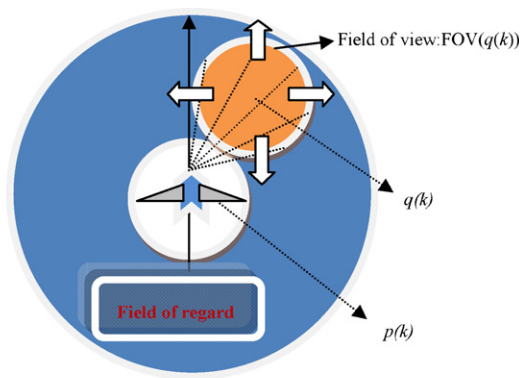

Fig. 1. Diagram of a field of view (FOV) and field of regard of the optical sensor.

UAV target search/ID problem has expanded from a 2-DOF or 3-DOF optimization problem for the UAV position, to a 4-DOF, 5-DOF, or 6-DOF optimization problem for the UAV and sensor position [4].

We present in this paper a restricted-direction target search approach that jointly optimizes routes and optical sensor orientations. We consider a single UAV, which is equipped with two optical sensors to view a limited region of the environment it is visiting, moving in geographic environment, searching for targets of interest and avoiding obstacles and threats. Our method computes paths considering actual maneuverability limitations of the UAV. This approach is coupled in that it evaluates paths based on optimization of the optical sensor tasks for the duration of the path.

2. Problem formulation

Consider a single UAV is searching for one or more targets in a bounded planar region $\Re \subseteq \mathbb{R}^2$. The UAV is equipped with two gimbaled optical sensors that can be steered around to view a limited area of the search region.

This section formulates the search problem as a discrete-time optimization in which the UAV and the optical sensor orientations are controlled in a way to maximize the probability of locating the targets in minimum time.

2.1. Restricted-direction UAV dynamics and sensor model

Denote the position of the UAV by $p(k)$, where $p(k) \in \Re$ is the UAV's position at time k, and k is a discrete time variable belonging to the nonnegative integers. We consider the actual kinematic model for the UAV, which can move only in a constrained region with a limited velocity owing to maneuverability limitations of its own, which constrain the maximum turning radius and the maximum turning angle. For each candidate path, we define a sensor task $q(k) \in \Re$ that specifies the starepoint where the UAV will point its optical sensor at time k. The field of view associated with a particular sensor task will generally depend not only on the orientation of the sensor, but also on the UAV's position and the characteristic of the sensor.

The instantaneous sensing region of the sensor on the ground, known as the field of view (FOV), is modeled as a circle "footprint", as shown in Fig. 1. The complete region on the ground that could be viewed by the camera as it is swept through its entire range of motion (while the UAV was stationary) is called the field of regard (FOR) of the optical sensor (see Fig. 1). The FOV will move around on the ground as a result of the motion the UAV platform and the steerable gimbaled mechanism that houses the sensor, determining whether the target is found or not. There are mechanical and practical limits on how far the sensor can be steered. The angular region between these limits is the camera's range of motion. Our final goal is to control the UAV and the optical sensor so that they move in a way that maximizes the probability of finding the targets in minimum time.

Suppose the UAV at position $p(k)$ aims its optical sensor at the point $q(k)$ at some instant at time k. A target located in the region FOV($q(k)$) will have a probability of being precisely detected by the sensor, which is generally referred to as the *probability of detection* of the optical sensor, and denote it by P_D. Furthermore, we assume that the probability of detecting a target that lies outside of the sensor's FOV is zero. The general detection function is defined as below:

$$D(q(k), x(k)) = \begin{cases} P_D, & x(k) \in \mathrm{FOV}(q(k)) \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

2.2. State estimation of targets

In order to optimize how the agents and sensors should move, a method is needed to estimate the probability distribution function (PDF) of $X(k)$ as it evolves over time. At each time step, the state estimator computes the best location $\bar{X}(k) = (\bar{x}(k), \bar{y}(k))$ with the highest target probability, but. In this paper, we assume that targets appear in the region around the best location $\bar{X}(k) = (\bar{x}(k), \bar{y}(k))$, with the probability of

$$f((x, y), k) = \frac{1}{\sqrt{2\pi\delta_x\delta_y}} \mathrm{e}^{-((x-\bar{x}(k))^2/2\pi\delta_x^2)+((y-\bar{y}(k))^2/2\pi\delta_y^2))} \tag{2}$$

where (x, y) is a point around $\bar{X}(k)$ and $f((x, y),k)$ represents the probability that the target appears at point (x, y) at time k.

Considering nonlinear target dynamics and environmental constraints such as obstacles and threats, this class of estimators is chosen, which includes grid-based probabilistic maps as well as particle filters. The estimator dynamics can be expressed in general form as

$$\begin{cases} x(k+1) = f_x(x(k), w(k), q(k)) \\ w(k+1) = f_w(x(k), w(k), q(k)) \end{cases} \tag{3}$$

where f_x and f_w represent the dynamic of the target state and the weight respectively.

2.3. Search reward

Thus far we have considered instantaneous probabilities of detection $D(q(k), x(k))$, but the quantity we wish to minimize is the time until the target is detected. This requires formulating a search reward function $r(k)$ in terms of a cumulative probability of detection. Let T^* denote a hypothetical time at which the target is found by the search agent, and the search reward as the probability that the target is found at time k is defined as follows

$$r(k) := P(T^* = k) \tag{4}$$

Thus, the search reward can also be expressed in further detail

$$r(k) := P(T^* = 0) = 0 \tag{5}$$

$$r(k) := P(T^* = k) = P(T^* \geq k)P(T^* = k | T^* \geq k) \tag{6}$$

Since the events of finding the target at different times are mutually exclusive, we can express $P(T^* \geq k)$, the probability that the target has not been found before time k, as

$$P(T^* \geq k) = 1 - \sum_{k=0}^{k-1} P(T^* = k) = 1 - \sum_{k=0}^{k-1} r(k) \tag{7}$$

Consequently, the search reward can be rewritten as

$$r(k) := \left(1 - \sum_{k=0}^{k-1} r(k)\right) P(T^* = k | T^* \geq k) \quad (8)$$

where $P(T^* = k|T^* \geq k)$ is the conditional probability that the target will be found at time k given that it was not found previously.

3. Restricted-direction coupled routing and optical sensor tasking optimization algorithm

Our proposed method is a restricted-direction target search approach in that we take into consideration the UAV's maneuverability limitations and environmental threats, which constrains the movement of the UAV. That means at each time step, the UAV must avoid threats and obstacles and can only choose paths in a limited region of a sector.

As the agent travels along a path P, it executes a series of specified sensor tasks, denoted by $S(P, k) := (q(k), q(k+1), \ldots, q(k+T_P))$. The route points $p(k)$ and sensor tasks $q(k)$ may be chosen arbitrarily or computed by an optimization algorithm, which allows for the following two possible methods of implementation. The traditional decoupled routing and sensor tasking optimization evaluates paths based on all search reward that lies within an agent's field of regard along the entire path. It requires much less computation, but when the speed of the agent is too fast for the sensors to view everything inside the agents' FORs, or urban scenarios with line-of-sight blockages, the performance of the approach will badly suffer [4]. In other words, the actual search reward collected in $S(P)$ is lower than in FOR(P) owning to some actual limitations like video tracking software processing speed and servos speed controlling sensor gimbals.

To improve the searching performance and maximize the probability of finding the target, the coupled routing and optical sensor tasking optimization algorithm solves the routing and sensor tasking problems jointly. At each time step k, we expand the current waypoint $p(k)$ and obtain the next *l-step* waypoints. For each candidate path P, an optimal sensor schedule $S^*(P)$ is selected. The score of $S^*(P)$ and the cost of path P is used to compare each candidate path P, and the selected path will be the one with the best score for an implementable schedule. Thus, in the coupled algorithm, candidate UAV paths are evaluated using a more accurate reward model.

The steps of the restricted-direction target search approach based on coupled routing and optical sensor tasking optimization are presented in Fig. 2.

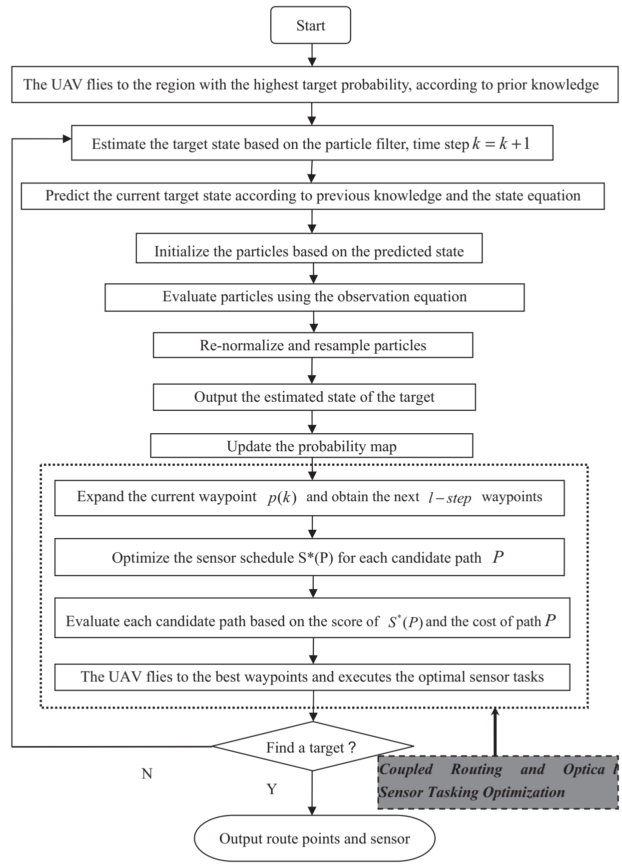

Fig. 2. The flow chart of the whole searching procedure.

4. Simulation results

Suppose a single UAV is searching a 100 km by 100 km square region $\Re$ for two static targets and a mobile one. The field of view of the optical sensor is modeled as a circle 1 km by diameter and the field of regard is a circle 3 km by diameter. Enemy threats and terrain obstacles are spread across the searching region $\Re$, including radar detection regions (Rf), mountains (M), bad weather regions (Bw) and no-fly zones (Fd) (see Fig. 3).

The UAV has a turning angle of 1.05 rad and can only move in a limited sector at each time step. The UAV flies a distance of 2 km before the next waypoint is computed and takes three measurements along the path. A simple particle filter is used to estimate the dynamic state of the targets.

Fig. 3 shows the searching path and the target movement trajectory. Solid dots represent the location where the targets are detected and found, while soft ones mark targets' initial location according to any prior knowledge. The simulation result shows that the UAV managed to detect and find two of the three targets while successfully avoiding threats and terrain obstacles. The third target is missed partly because the UAV has a flight limitation and has to abandon the region after a certain times of search. In addition, inaccuracy of the optical sensor involving detection probability and false detection can also lead to the target being missed (see Figs. 4 and 5).

Denote the number of detected and found targets, the total length of the searching path and the searching times for each target by N, L and S_i. The comparison results in Table 1 show the coupled routing and optical sensor tasking optimization algorithm yield significantly better results than the decoupled one, which should be

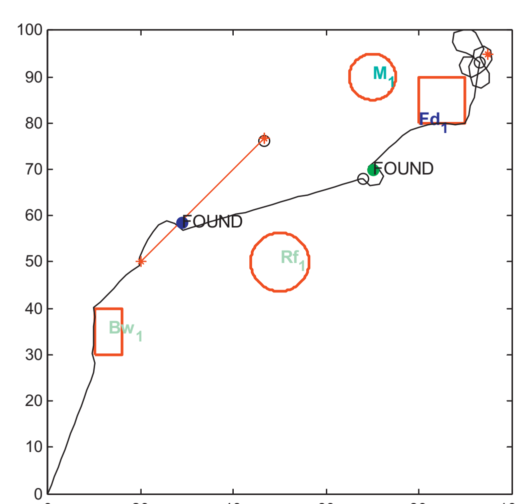

Fig. 3. A snapshot of the searching path and target movement trajectory.

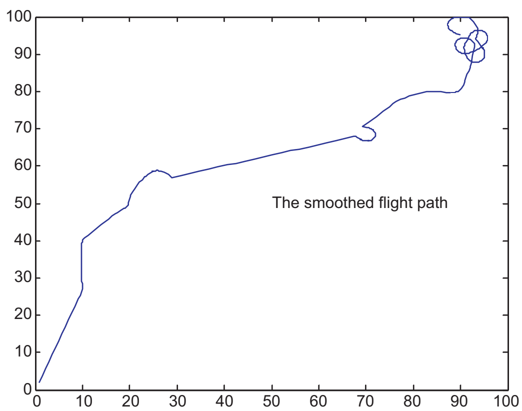

Fig. 4. A snapshot of the smoothed searching path.

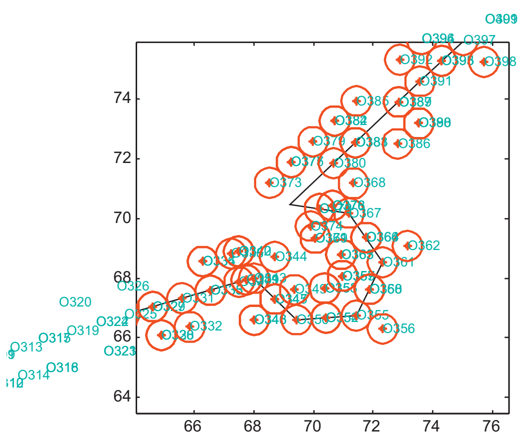

Fig. 5. A snapshot of the sensor tasks along the path.

Table 1
Algorithms performance comparison.

Method	N	L (km)	$S_1/S_2/S_3$
Coupled routing and optical sensor tasking optimization	2	192.8055	8/5/30
Decoupled routing and optical sensor tasking optimization	1	238.1766	8/30/30

contributed to the fact that in the coupled algorithm, candidate UAV paths are evaluated using a more accurate reward model.

5. Conclusions

The target search problem is a key issue in UAVs and UAV-mounted sensor control, which involves control of the UAV to avoid obstacles and threats and manipulation of the optical sensor to locate targets of interest in minimum time. In this paper, we proposed a restricted-direction target search approach based on coupled routing and optical sensor tasking optimization. The UAV moves in the dynamic environment, searches for targets of interest, and is capable of avoiding obstacles and threats immediately. The paths are obtained considering actual maneuverability limitations of the UAV and are evaluated according to optimization of the optical sensor tasks for the duration of the path. Series of comparative experimental results demonstrate that this algorithm makes effective use of the coupled method of optimization and performs significantly better than previously proposed approaches.

Our future work will focus on how to apply the presented algorithm to the actual search task of a UAV and try to improve its whole performance.

Acknowledgements

This work was partially supported by Natural Science Foundation of China (NSFC) under grants #60975072 and #60604009, Program for New Century Excellent Talents in University of China under grant #NCET-10-0021, Open Fund of the State Key Laboratory of Virtual Reality Technology and Systems, Beijing NOVA Program Foundation of China under grant #2007A017, Aeronautical Foundation of China under grant #20115151019, the Fundamental Research Funds for the Central Universities of China under grant #YWF-11-03-Q-012 and YWF-10-01-A18, and Graduate Innovation Foundation of Beihang University (BUAA). The authors also want to show thanks to the anonymous referees for their valuable comments and suggestions, which lead to the better presentation of this work.

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