

Aerial Vehicle Search Path Optimisation Using Baye's Theorem

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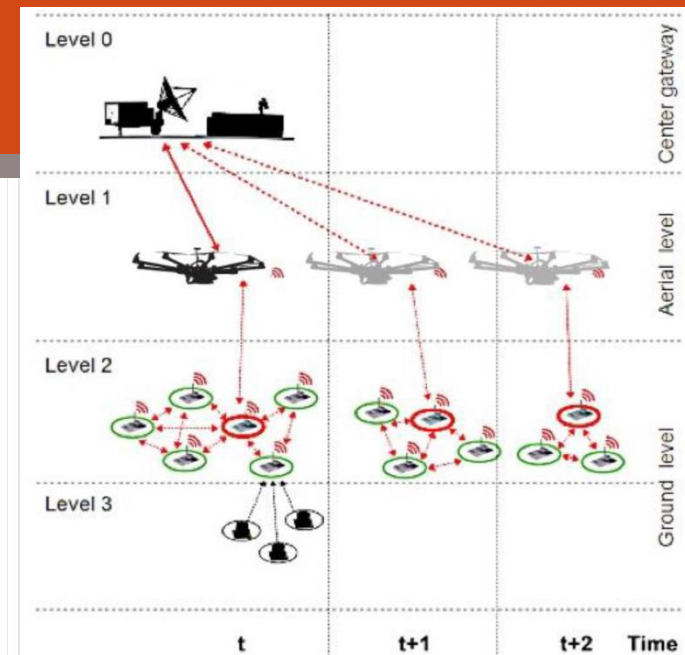
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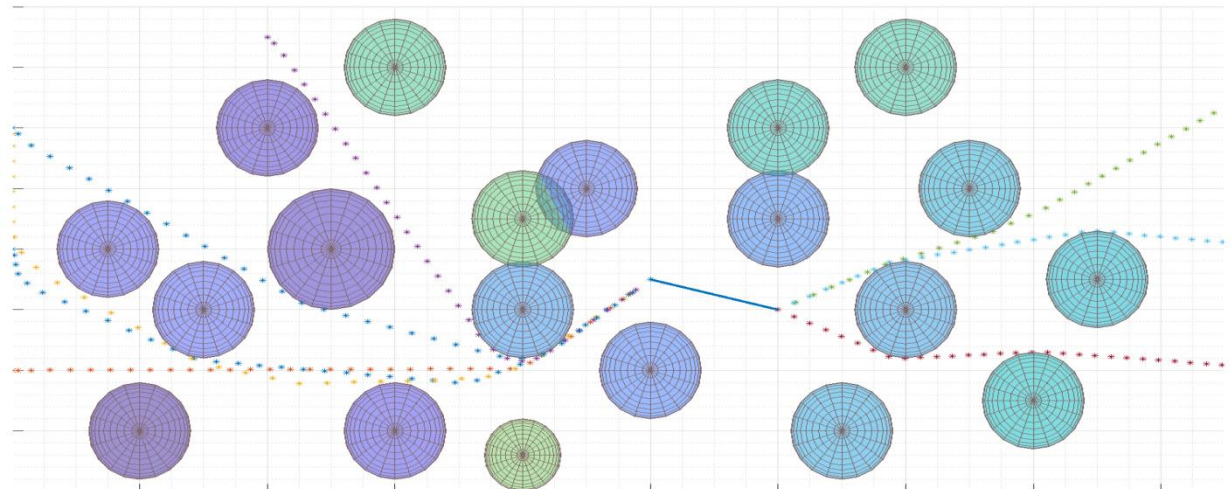
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Introduction

The project proposes a search path optimisation for moving target by any aerial vehicle. Let us consider a disastrous situation like a plane crash at sea where the only information about the crash site comes from the flight plan, maybe supplemented with a Mayday call.

Among all survivors, some may have managed to get in a life raft, which maybe drifting as it is subject to winds and currents.

In such a case, it is not sufficient to just fully cover the search area, since it is possible for the life raft to move into an area that has already been observed.

To increase the chance of survival, efficient planning methods are required.

With the ongoing technological development of unmanned aerial vehicles(UAVs), the idea of employing a UAV for search has risen.



Objectives

Unmanned aerial vehicle(UAV) is a type of aircraft that can be remotely controlled or fly autonomously following on a preplanned flying routes with no onboard pilots. UAV has

found increasing number of applications in real-world environments. With the incessant improvement of the intelligence of the UAV, the application of UAV has been greatly expanded during the past years. The tasks for UAV to perform are diversified, such as communication relay and air striking. It is also used by the military personnel for target tracking, intelligence gathering about enemy. It can also be used by the geological department to carry out geological operations and post earthquake resources.



Bayes' Theorem:

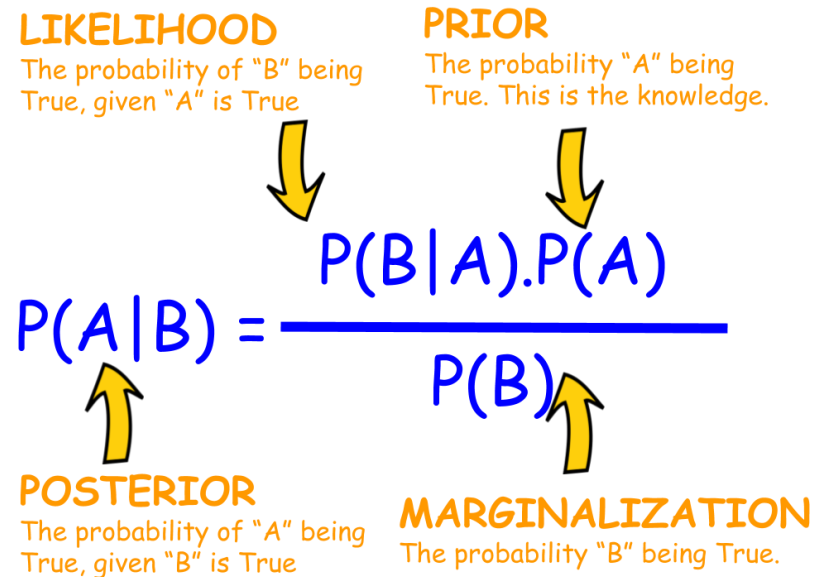
- Bayes' Theorem can be mathematically stated as:

$$P(A | B) = \{P(B | A)P(A)\} / \{P(B)\}$$

Where, A and B are the events

And $P(B) \neq 0$

- $P(A | B)$ is a conditional probability: the likelihood of event A occurring given that B is true
- $P(B | A)$ is also a conditional probability: the likelihood of event B occurring given that A is true
- $P(A)$ and $P(B)$ are the probabilities of observing A and B respectively; they are known as the marginal probability.
- A and B must be different events.



Working Methodology:

- The Target Model:

This moves with respect to time. We make use of a grid based probability map(pc_k). The target occupies one cell c_k at time k . So, pc_k gives the probability of the target vehicle at position c_k and time k . Here, we use:

$$pc_{k+1}(c) = \sum_{c' \in C} d(c', c) pc_k(c')$$

- The Sensor Model: This is used to take observations. Here two observations are seen for-

$$Z_{c,k} = \begin{cases} 1 & \text{: if platform detects the target} \\ 0 & \text{: else} \end{cases}$$

The glimpse probability $pg_k = P(Z_{c,k} = 1)$: It represents the probability of target detection

The overlook probability $po_k = P(Z_{c,k} = 0)$ or,

$1 - pg_k$: It represents the complement of glimpse probability i.e. the probability of overlooking target.

- From the above equations,

$$pc_{k+1}(c) = \sum_{c' \in C} d(c', c) pc_k(c')(1 - pg_k(ok, c'))$$

- The Platform Model: The object to be tracked here is an aerial platform which is in motion.

$$X_{k+1} = X_k + S_k \cdot \cos (\theta_k + \alpha_k)$$

$$Y_{k+1} = y_k + S_k \cdot \sin (\theta_k + \alpha_k)$$

Conclusion

- Several recent cases, especially emergencies at sea, have shown the high importance of acquiring knowledge about the location of a target. Natural disasters, extreme cases in air transport and the shipping industry as well as terroristic threats, are the basis for possible scenarios of interest. Many of these scenarios can have disastrous consequences when the target is not found (in time). Effective search-path optimization methods are therefore needed. We presented a novel approach, consisting of a binary integer linear program (BILP) solution, embedded in an iterative framework. We ran simulations for several search-path lengths and compared the performance of our approach to a well-established method for search-path planning.

. Results show that our approach yields better results on all test instances, however at increased computational costs. Some time for optimization is available though, since it is performed during the execution of a previously planned search-path.

The main goal of this paper was to introduce and demonstrate the new mathematical formulation. As a consequence, we did not focus yet on improving the computation time. This may be accomplished by the development of a customized algorithm, which is the aim in further research.