Chapter 7

A HOSPITABILITY MAP APPROACH FOR ESTIMATING A MOBILE TARGETS LOCATION

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Abstract The following problem is considered. An air vehicle detects a mobile target using its own sensor(s), but delays attack. While the target is being detected, the air vehicle takes several looks at the target, thus producing target state estimates. Some time later (on the order of minutes), the same or another air vehicle views the target area again. The target is not detected on the second set of looks. We assume that it has moved. Since the target has moved away, where should we look for it? This is a prediction and search problem. Prediction uses historic information to predict the future states (location and kinematics), and search is to look for the target based on the prediction results. Since we assume that the time separation between the two set of looks is quite significant, traditional prediction based on historic kinematics information alone will not work well. The target kinematics information is diluted quickly as the radius of possible target locations from that of the first set of looks gets bigger. However, the previous kinematics (target route history) at least provides a center location for future possible target locations. As will be shown, we can rely on terrain-based state prediction to determine the likelihood of the new target position. The effects of the terrain are captured by something known as a hospitability map. A hospitability map provides a likelihood or a "weight" for each point on the earths surface proportional to the ability of a target to move and maneuver at that location.

Keywords: Prediction, search, motion models, hospitability map

1. Introduction

The overall objective of this research is to explore innovative modeling and estimation techniques that result in more robust estimation when model uncertainties exist. With this overall goal in mind, we are pursuing research problems in the area of uninhabited autonomous vehicles (UAVs), The problem studied here was proposed by AFRL/VA and is described below.

An air vehicle detects a target using its own sensor(s), but delays attack. Some time later (on the order of minutes), the same or another air vehicle views the target area again. The target is not detected on the second look. There are three possibilities why the target was not detected on the second look. (a) The first vehicle did not actually detect the target in the first look; it was a false detection. (b) The target is still there, but the second vehicle could not detect it; it was a misdetection. (c) The target moved. In the work presented here, we assume case (c) that the target moved.

Since the target has moved away, where should we look for it? This is a prediction and search problem. Prediction uses historic information to predict the future states (location and kinematics), and search is to look for possible future states based on the prediction results. As the elapsed time gets bigger, the difference between prediction and search becomes blurrier. So we need to design a technique that uses both prediction and search, either simultaneously or alternatively.

Because the time separation between two looks is quite significant, traditional prediction simply based on historic kinematics information will not work. The target kinematics information is diluted quickly as the radius of possible target locations from that of the first look gets bigger. However, the previous kinematics at least provides a center location for the possible target locations.

As will be shown, we can rely on terrain based state prediction to determine the likelihood of the new target position. The effects of terrain are captured by something known as a hospitability map [1, 2, 3] A hospitability map provides a likelihood or a "weight" for each point on the earths surface proportional to the ability of a target to move and maneuver at that location. Here high hospitability map values denote that a target can move and maneuver quickly over the corresponding terrain. Likewise, low hospitability value indicates that a target cannot easily move over that terrain. The following factors are considered in deriving a hospitability value; slope, surface roughness, transportation, geology, landform, soil, vegetation, hydrology, urban areas, and climate.

2. Approach

2.1. Propagation of the probability density

The first UAV's look at the target provides an initial probability density (assumed to be a joint Gaussian) of the target's location. Since we have only one look at the target, we cannot make any assumptions about the velocity and heading of the target when it moves. The best we can do is to model the movement as a diffusion process in all directions as characterized by the following Ito equations

$$dx = \delta\beta_x \tag{1}$$

$$dy = \delta\beta_y \tag{2}$$

where dx and dy are scalar white Brownian motion process. The probability density of the targets location based upon the Ito equations is given by the following partial differential equation called the Fokker-Planck equation.

$$\frac{dp}{dt} = \frac{\sigma_x^2}{2}\frac{\delta^2 p}{\delta x^2} + \frac{\sigma_y^2}{2}\frac{\delta^2 p}{\delta y^2} \tag{3}$$

This section is concerned with the numerical solution of the Fokker-Planck equation over the rectangular region $0 < x < a, 0 < y < b$, where p is known initially, based upon the first look at the target, at all points within and on the boundary of the rectangle. Also, it is known subsequently at all points on the boundary. Define the co-ordinates, (x, y, t), of the mesh points as

$$x = i\Delta x \qquad\qquad y = j\Delta y \qquad\qquad t = n\Delta t \tag{4}$$

where $i,\ j,\ and\ n$ are positive integers, and denote the values of p at these mesh points by

$$p(i\Delta x,\ j\Delta y,\ n\Delta t) = p_{ijn} \tag{5}$$

The explicit finite-difference approximation of Equation 3 is given by

$$\begin{aligned}\frac{p_{i,j,n+1} - p_{i,j,n}}{\Delta t} &= \frac{\sigma_x^2}{2(\Delta x)^2}[p_{i-1,j,n} - 2p_{i,j,n} + p_{i+1,j,n}] \\ &+ \frac{\sigma_y^2}{2(\Delta y)^2}[p_{i,j-1,n} - 2p_{i,j,n} + p_{i,j+1,n}]\end{aligned} \tag{6}$$

Solving for $p_{i,j,n+1}$ yields:

$$p_{i,j,n+1} = p_{i,j,n} + \Delta t \left(\frac{\sigma_x^2}{2(\Delta x)^2} [p_{i-1,j,n} - 2p_{i,j,n} + p_{i+1,j,n}] + \frac{\sigma_y^2}{2(\Delta y)^2} [p_{i,j-1,n} - 2p_{i,j,n} + p_{i,j+1,n}] \right) \tag{7}$$

which is valid only when

$$\Delta t \left(\frac{\sigma_x^2}{2\Delta x^2} + \frac{\sigma_y^2}{2\Delta y^2} \right) \leq \frac{1}{2}$$

2.2. Hospitability map as a measurement

Once we have propagated the probability density function (pdf) for the target location, we apply the hospitability map as a measurement at every time instant $(n\Delta t)$ to "constrain" the pdf to regions of high hospitability. This operation is characterized by the following update equation

$$p_{i,j,n}^{+} = \frac{1}{c} p_{i,j,n}^{-} H_{i,j} \tag{8}$$

where the "-" is used to denote the unupdated pdf and the "+" is used to denote the updated pdf, c is the normalizing constant, and $H_{i,j}$ is the i^{th}, j^{th} cell of the hospitability matrix. This updated pdf is used in propagating to the next time instant.

2.3. An optimal search strategy

In developing an optimal search strategy, we decided we wanted to minimize the distance moved and maximize the probability density of the next search cell. Consequently, we developed a search strategy based upon minimizing the following cost function over all cells (i,j)

$$J_{i,j} = W_1 \ \textit{Distance to cell } (i,j) + \frac{W_2}{\textit{Probablity that the target is in cell } (i,j)} \tag{9}$$

where W_1 and W_2 are weighting factors.

3. Simulation Results

3.1. Propagation and update

Figure 7.1 below shows the results of propagation and update over a 300 second period of simulation. Notice the pdf seems to "flow" around the small values of hospitability as desired. A human looking at the hospitability map might make a similar prediction, however the UAV must do this in an automated fashion. Next we look at how to use these results to develop an optimal search strategy.

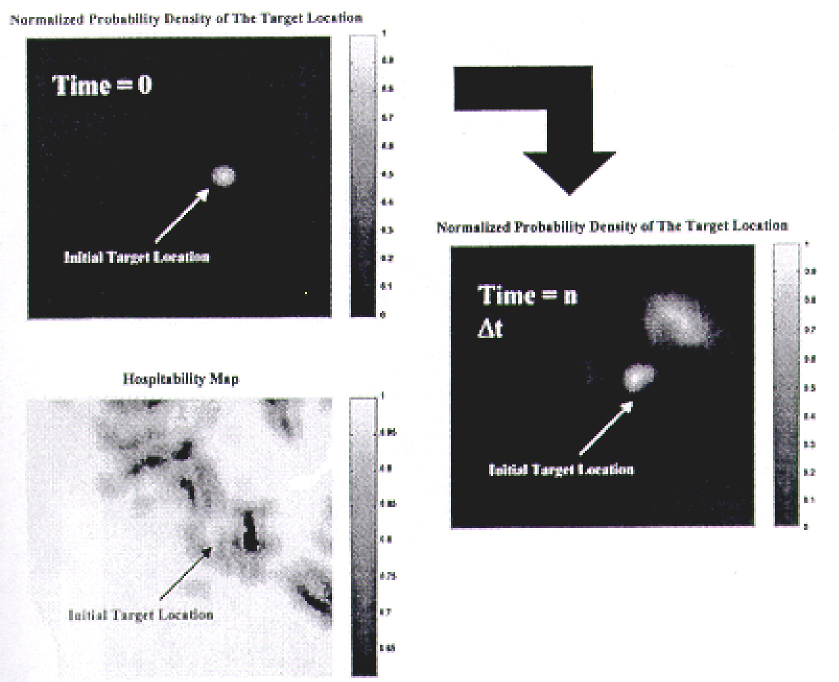

Figure 7.1. Simulation results

3.2. Search strategy results

In this research, we optimized the search cost function by exhaustively computing its value over every cell. For comparison, we used a gradient decent algorithm . Future research, we will look for more efficient methods of doing this optimization. When a cell is searched and nothing is found, the algorithm will zero out that cell and all the cells it passes over in getting to that cell (also assuming nothing was found). It is set to zero because we know with high certainty that the target is not there if not detected.

Figure 7.2 below, shows the results of the exhaustive search strategy as applied to the example in Figure 7.1. Recall in this example the simulation time was set to 300 seconds. To simulate the fact that the search UAV does not arrive on the scene until sometime later, we start the search at 150 seconds into the simulation. The search begins at the location where the first UAV found the target.

Notice in Figure 7.2 that the algorithm produces a tri-modal pdf. Also notice in Figure 7.2, that the search algorithm basically zeros out the "first" mode of the probability density before "plowing" a path through the "larger" mode of the pdf. This behavior seems very natural and sensible from a humans point of view. However, the UAV must be able to do this anonymously

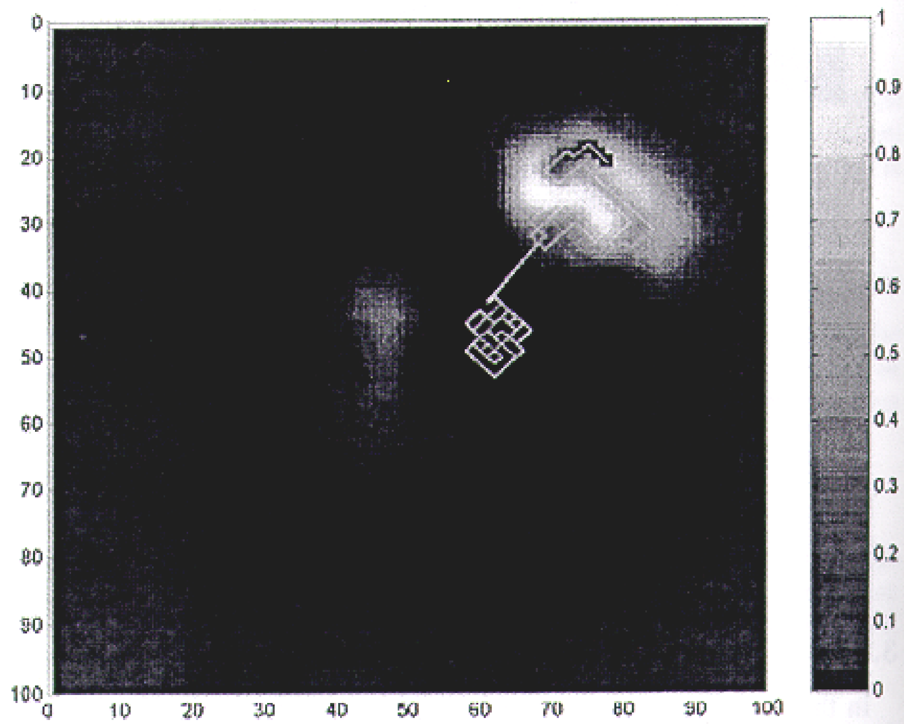

Figure 7.2. Simulation results of exhaustive search (The white lines represent the search path

Figure 7.3 shows the response of a gradient decent approach to solve the search optimization. Notice that the search vehicle never leaves the first mode. It gets trapped in a local minimum. However, it may be possible to change this behavior by applying techniques such as genetic algorithms to force the algorithm to look in different areas of the search space.

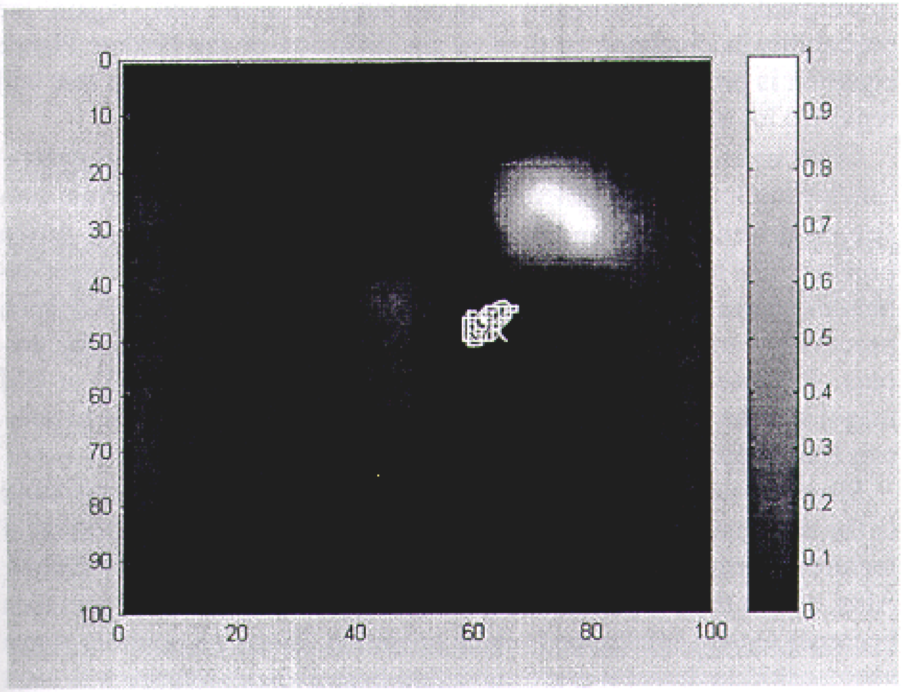

Figure 7.3. Simulation results of gradient descent search (The white lines represent the search path

4. Future Research

In future research, we will look for more efficient methods of doing search optimization. When a cell is searched and nothing is found, the algorithm zeros out that cell probability and all the cells it passes over in getting to that cell (also assuming nothing was found). It is set to zero because we know with high certainty that the target is not there if not detected.

Notice in optimizing the search we chose an optimization scheme based on cost of each individual cell. However, since we are able to look at cells along the way to the optimal cell, what is really needed is a cost function that considers the cost of the whole path from cell to cell. Further the cost of each cell is changing in time as the diffusion of the Fokker Planck equation is propagated.

The search algorithm has some properties analogous to a weighted travelling salesman problem. For example, there is the distance between each cell in the search space that we want to minimize and each cell is weighed by the probability that the target is in the cell. Again, the probability is changing in time as the diffusion of the Fokker Planck equation is propagated. Hence this is a very complex problem that will require a lot more work to solve effectively.

Other areas we will pursue in the future is multiple hypothesis generation/testing hypothesis generation. This is a kinematics and terrain constraints driven process and the hypothesis validation is a feature driven process. The hypothesis generation could be imbedded in the target dynamics modeling (nonlinear and hybrid) and the hypothesis validation process is carried out in the kinematics and ID feature updating process. Because of low resolution nature in terrain maps (DTED or HM maps) and the multi-directional motion of the target, a multiple hypothesis testing approach is most suitable.

Since we need to find out if the target we detected in the later looks is the one that we detected in the first look, effective incorporation of feature information in the updating/validating process is very crucial. Also, as the time separation is getting bigger, the prediction operation becomes more a constrained search operation. Since the possible search space could be huge, a multiresolution-based search approach is most desirable. Further, we proposed using different propagation methods for the Fokker-Plank equation such as the particle filter and the Gaussian wavelets estimator (GWE) which is an efficient finite dimension approximation for the hybrid densities.

References

[1] K. Kastella and C. Kreucher, "Ground target tracking using a multiple model nonlinear filter," *accepted by IEEE Transactions on Aerospace and Electronic Systems*, 2003.

[2] C. Kreucher and K. Kastella, "Multiple model nonlinear filtering for low-signal ground target applications," *Proceedings of SPIE AeroSense, Signal and Data Processing of Small Targets*, Orlando, Florida, April 2001.

[3] K. Kastella, C. Kreucher, and M. Pagels, "Nonlinear filtering for ground target applications," *Proceedings of SPIE AeroSense, Signal and Data Processing of Small Targets*, Orlando, Florida, April 2000.