Threat Modeling for Sensor Optimization

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***Abstract*— The Navy and other US government entities (e.g., Drug Enforcement Agency, Homeland Security, Border Patrol) frequently must design and manage distributed sensor fields to search for targets over large areas. Field performance is often based solely on sensor coverage or probability of detection evaluations, which provide only a fleeting snapshot of how the field is performing at a particular time. This paper describes an efficient and more tractable approach to evaluating the performance of distributed sensor fields. Given *a priori* target probability distributions and sensor measurements distributed in time and space, the approach directly scores entire sensor fields based on their ability to detect threats and process false alarms. It maintains an historical record of areas searched, from which cumulative coverage can be computed. It has been used to manage 2- or 3-dimensional target/threat probability density functions moving through distributed sonar fields, with sensor performance updated to reflect real-time feedback of environmental and field conditions. This work will focus on a marine security and defense scenario.**

I. Introduction

Under D&I efforts funded by ONR Code 321, an accurate and efficient Fokker-Planck (FP) approach was pioneered as an alternative to Monte Carlo simulation (MCS) for modeling temporal and spatial threat probability density function (PDF) evolutions [1], [2]. This approach was applied to managing and optimizing multistatic sonar distributed sensor fields. In [3], the FP formulation was refined to advance 3-dimensional PDFs of arbitrary shape with drift (average motion) and diffusion (spreading) in the presence of moving sensor fields. The Probability of Target Presence (P_T) for an ocean area-of-interest was represented in three dimensions using voxels (volumetric pixels). The P_T was computed for each voxel from *a priori* target distributions. P_T values were updated for target motion using an efficient FP equation digital filter method [4]. Target Probability of Detection (P_D) was computed for each sensor at each voxel, and Bayes' rule was used to update the P_T given sensor measurements and their associated P_D's. This approach allows for a variety of operational goals to be evaluated, including sensor deployment effectiveness and sensor field leakage, through simulation, in very reasonable computational time. This approach is flexible and works with arbitrary sensors in any domain such as Border Security. For this paper, it will be applied to a marine security and defense scenario.

A similar approach to evaluating field performance is presented by Incze [5], which uses a Bayesian method and Monte Carlo simulations to evaluate field performance. Monte Carlo simulations are formed by sending many targets with random velocities and bearings through a field of sensors and collecting statistics on detections. This type of Monte Carlo analysis is computationally demanding. One of the motivations behind the work in this paper is to present an alternate method to Monte Carlo that is less computationally demanding.

Section 2 will summarize the ocean model description. Section 3 will discuss the threat models developed and used for the simulations. Section 4 will present simulation results for a marine security and defense scenario. Section 5 will summarize the paper and discuss areas of continued work.

II. Model Description

The management of distributed sensor fields in an ocean environment requires a model that can keep track of position and sensor performance. Directing sensor placement and activation for efficient target detection and tracking requires an updated prediction of potential target locations. In this work the probability model is implemented on a two-dimensional grid with multiple layers for various threat models. Ocean environmental information is included in the sensor performance predictions. Real time feedback from sensor returns and probabilistic propagation models are used to update P_T values. The basis for the propagation model was described in [2], and is briefly described below.

A. Probability of Target Presence

Here, a metric called "Probability of Target Presence," $P_T(x, y)$ is defined. This should be interpreted as the probability that a target is present at discrete geographic coordinate (x, y). P_T equal to one means that there is a good chance a target exists and there is no evidence to the contrary. A P_T of zero indicates that a target does not exist at the given location due to sensor measurements or *a priori* information. P_T equal to 0.5 would then correspond to an unknown state or equally likely target state. The search area is discretized into cells of equal size, which are assigned an *a priori* probability of target presence. This formulation accounts for the sensor P_D against the target presence model, assuming that there are no detections. Using Bayes theorem, the probability of target presence given no detections is defined as

$$P_{T|ND} = \frac{P_{ND|T} P_T}{P_{ND|T} P_T + P_{ND|NT} P_{NT}}, \tag{1}$$

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where ND denotes no detection, NT denotes no target present, and T denotes target presence. Substituting the probability of detection and the probability of false alarm into Eq. 1 gives the following:

$$P_{T|ND} = \frac{(1 - P_D)\, P_T}{(1 - P_D)\, P_T + (1 - P_{fa})\,(1 - P_T)}. \tag{2}$$

P_D is the probability that we detect a target when a target actually is present, and P_{fa} is the probability that we decide a target is present when there is no actual target (false alarm).

Sonar performance predictions are typically calculated in terms of signal excess (SE) via manipulation of the sonar equation [6]. Signal excess is defined as the signal-to-noise ratio (SNR) minus a detection threshold (DT), where DT is set based on design values of P_D (usually set to 0.5) and P_{fa} (usually set to a very low number, like 10^{-5}). Signal excess equal to 0 dB corresponds to the design value of P_D. Analytic representations are available to calculate P_D for other values of SE. See [7] [8] [9] for further discussion on this topic. The SE data used in these simulations are generated by a standard acoustic model.

The *a posteriori* $P_{T|ND}$ for the given sensor coverage becomes the *a priori* value of P_T for the next time step. The time step can be defined as a discrete change in time (such as every 60 seconds) or whenever there is a sensor measurement. This approach keeps track of search efforts, and can be used for optimizing future search.

B. Moving Targets

The formulation for $P_{T|ND}$ as so far discussed does not account for targets moving into an area that has already been searched or any other target motion. Moving targets are accounted for based on an approach by Kanchanavally *et al.* in [10], where a diffusion process is modeled using the Fokker-Planck equation and Brownian motion. In [2], the approach was extended to account for average target motion. The Fokker-Planck (FP) filter, derived in [2], is applied to more complex threat types in the current work. Various threats can be injected into the P_T surface based on scenario requirements. The current work includes three different types of threats which will be discussed below.

III. Threat Types

There are three types of threats modeled in this work which can be seen in Figure 1. The first is a Gaussian shaped threat detection which may occur based on various detection methods or *a priori* information. This threat type can incorporate various Area of Uncertainties (AOU) and target velocities. The second type of threat that is modeled is the line threat. The line threat is used if there is information about targets coming from a particular area. This is analogous to the barrier problem where the line threat represents targets possibly penetrating a barrier. The last type of threat is background, which represents possible targets in the area of interest. This is typically set to a constant probability of .5 or lower depending on the mission. The Gaussian and line threats are illustrated in the next section and are a new addition to the P_T approach of previous work.

IV. Application Description

The P_T and FP filter algorithms are applied to a distributed sensor field where several threat models are incorporated. This simulation is analogous to a marine security and defense problem where threats are approaching from a known direction (Line threat) with possible known targets in the area already (Gaussian threats and background). The goal of the scenario is to see if the various threats can be detected as they travel trough the sensor field. Although this metric can be used for sensor management and ping planning, in this scenario, the P_T map was used to illustrate the effectiveness of the sensor field.

The scenario has four sensors with direct path and convergence zone (CZ) detection regions. The sensors are drifting at 1 knot at a compass heading of 0 degrees. There is a line threat coming from the West which can represent the barrier problem where distributed sensors are put in place to protect a particular area of the ocean. The line threat can also represent *a priori* knowledge of targets approaching from a general direction. The line threat has a speed of 5 knots at a heading of 90 degrees. The northern Gaussian threat is moving at 5 knots with a heading of 90 degrees and the southern Gaussian threat is moving at 5 knots with a heading of 45 degrees. There is also a small velocity associated with the background probability, which represents *a priori* information about the general motion of targets in the area of interest. This scenario is intended to be generic to illustrate the possible use of this overall approach, and is not meant to be 100% consistent with a real scenario.

Figures 1 through 4 are four snapshots in time of the simulation. The gray scale regions represent the Probability of Detection(P_D), where lighter gray is the better coverage. The red/blue area represents the P_T map. Blue represents low P_T ($P_T = 0$) and red represents high P_T ($P_T = 1$). The simulation area is approximately seven degrees by 9 degrees, represented by a grid of 673x673 cells. There is a P_T layer for each threat, however all are shown together in the figures as the max of all P_T layers. In this scenario there are 4 layers representing the four different threats (2 Gaussian, 1 line, and the background threat).

In Fig. 1, the scenario is just starting so the threats have not moved yet and the overall background P_T has not been cleared yet. The threats are propagated using the FP filter and the Bayes updates process described above. As time progresses, shown in Fig. 2, the line threat is moving East and the Gaussian threats have started to move as well according to their velocities. The southern Gaussian threat has been partially cleared by two of the sensors. It should be clear that the Gaussian threats are no longer Gaussian after sections are detected and cleared from the area. As time progresses even further in Fig. 3 and 4, the line threat has moved and diffused quite a bit into the detection regions of the sensors and much of the line is being cleared in those regions. Although the bulk

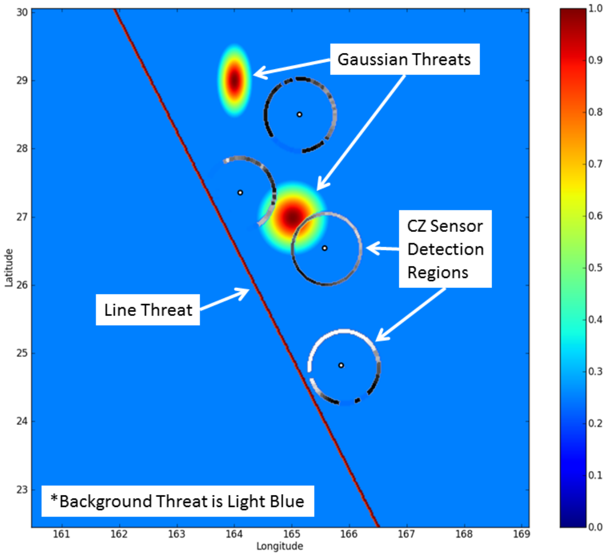

Fig. 1. Probability of Target Presence (P_T) Map at the first ping (assumes all sensors ping at the same time at regular intervals). The color bar shows the level of P_T from zero to one. There are 4 sensors and their coverage is shown in gray scale, the lighter gray the better the coverage. There are 3 types of threats (2 Gaussians, 1 Line, and a Background threat).

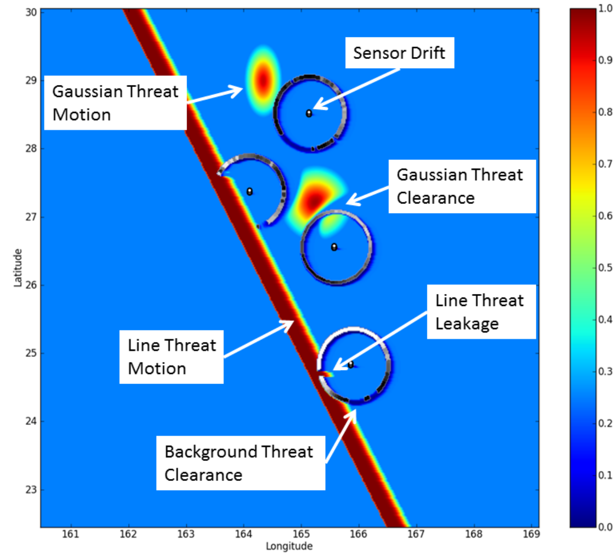

Fig. 2. Probability of Target Presence (P_T) Map after two minutes and several pings. All the threats have moved according to their associated velocities, and the threats have been cleared according to their sensor coverage.

of the coverage is from CZ, the direct path can be seen in Fig. 4. There is a streak of cleared P_T from the direct path (the direct path coverage is labeled in the figure).

The figures also show the leakage for the various threat types. The gaps in the CZ coverage become very evident as streaks of the line threat pass all the way from East to West in the simulation. This approach can be a valuable tool for evaluating how effective coverage is for various scenarios. Although the sensors do detect large parts of the line threat, there is a lot of leakage. For this simulation, it is clear the sensor placement is not very good for a barrier type scenario. A few more sensors could be added to prevent leakage, or perhaps sensor deployment locations could be changed to improve coverage.

A. Computational Considerations

In order for this approach to be viable in a real system, the model will need to be computationally efficient enough to run at real time. The simulation for the scenario described above runs anywhere from 40x to 100x real time on a single Intel Xeon 2.8 GHz processor. Some aspects of this approach have been parallelized for further improvement above 100x real time but are not reported here. The variability between 40x and 100x real time is due to the computational load of the sensor performance prediction.

V. Conclusions

In this work the P_T map and FP filter approach showed the effectiveness of the sensor field as well as places where targets could slip through for a Marine Security and Defense scenario. The simulations show a more realistic version of this approach compared to past work. New threat types were explored and shown in the simulation. This approach allows for the inclusion of other threat models as well. The P_T map was able to show the effectiveness of the sensor field as well as places where targets could slip through. This approach is intended as an optimization tool for the placement of sensors and sensor management. In future work we will look to apply this method to various sensor management problems for distributed sensor fields.

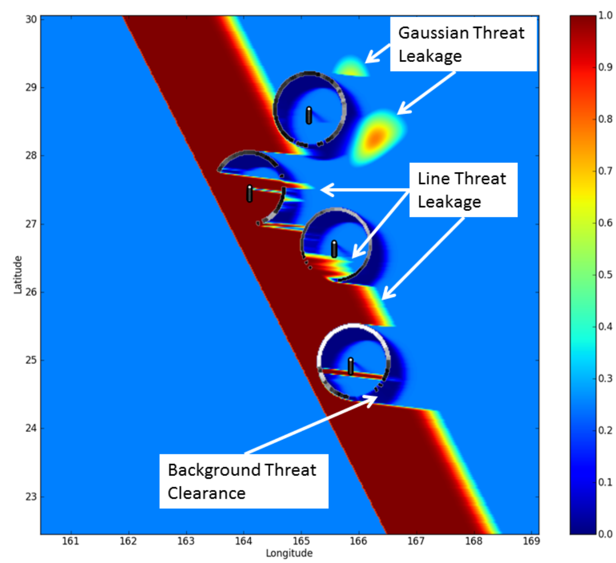

Fig. 3. Probability of Target Presence (P_T) Map after several more minutes. One of the Gaussian threats (no longer Gaussian) has been almost cleared, and the leakage from the sensors is evident.

There are limitations due to the the finite difference methods used (not discussed in this paper), however other approaches

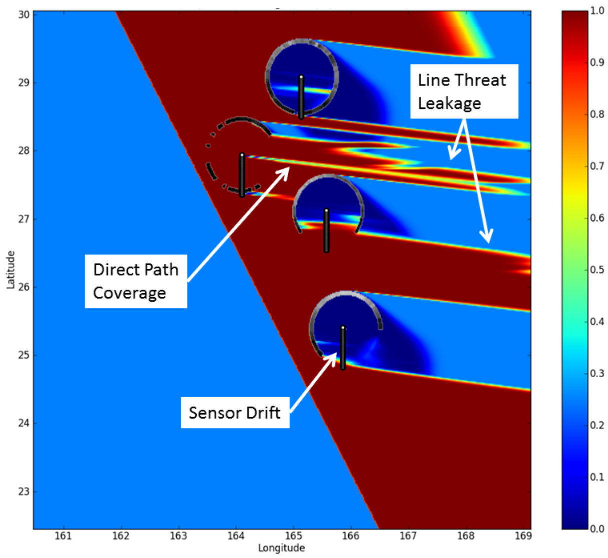

Fig. 4. Probability of Target Presence (P_T) Map after several hours. The Gaussian threats have moved out of the area of interest. The leakage from the line threat illustrates the non-effectiveness of the sensor barrier.

will be explored in future work. There is ongoing work to look at analytical solutions to the FP equations and see how those can be applied to this approach [11]. The computational efficiency of the filter approximation is much faster than a MC approach, however there is continued interest in speeding up this process even more. One approach we will look at is running these algorithms on a GPU where convolution (at the core of the FP filter) is highly efficient.

Acknowledgments

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