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Targeting an Asymmetric Maritime Threat: Workshop Report

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TARGETING AN ASYMMETRIC MARITIME THREAT:
WORKSHOP REPORT

by

Eva Regnier and Dashi Singham

January 2013

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ABSTRACT

Due to evolving maritime threats, including submarine warfare, piracy, smuggling, and coordinated attack by small vessels, several groups are actively developing tools to optimize the allocation of naval forces to detect and interdict maritime targets, and to provide decision support to commanders in countering these threats. This document reports on a workshop that brought together researchers from several optimization groups and environmental information groups to determine the degree of overlap in their problems. Many common challenges to implementation were identified. The results include a general formulation of the problem of allocating surface, air and undersea assets in a maritime environment that applies to many mission areas. The formulation includes informational input that combines target position and detection or interdiction capability. This allows the separation of the production of environmental information, including asset performance and target positions, from the optimization of asset allocation. Feedback between information production and optimization may occur relatively infrequently. This overcomes some of the practical challenges in implementation of decision support systems that the workshop participants identified. The recommendations identify important open questions and indicate that there is potential for benefit from collaboration and dissemination of advances on the common challenges.

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I. INTRODUCTION

A. PURPOSE

Due to evolving maritime threats, including submarine warfare, piracy, smuggling, and coordinated attack by small vessels, several groups are actively developing tools to optimize the allocation of naval forces to detect and interdict illicit vessels, and to provide decision support to commanders in countering these threats. Several similarities suggested, however, that research addressing these mission areas would benefit from a focused exchange among researchers and an effort to identify research directions that will have a broad impact across many mission areas.

First, at least at a superficial level, these mission areas have many common features, including similarity in the nature of the threat, the types of decisions and courses of action to respond to the threat, the type of information that is or should be exploited in making the decisions, and some implementation challenges. Second, several parallel efforts in optimizing asset allocation are ongoing and reported in distinct literatures; therefore, there may not be sufficient cross-pollination among these researchers. Third, efforts to develop more complete and accurate environmental (to include target) information have been largely separate from the development of optimization algorithms. It is rare for researchers working on generating information to interact with researchers working on how best to use the information.

Therefore, Eva Regnier and James Hansen called a workshop at the Naval Postgraduate School on March 13 and 14, 2012, to gather a focused group of researchers addressing different parts of this problem. We brought together researchers working on generating the information with researchers working on how to use it. The participant list is given in Appendix A. The primary goals were to:

- determine whether the mission areas are fundamentally different, or whether they are versions of the same problem;
- decompose the problem such that each group can continue to advance their work while maintaining interoperability; and
- identify the landscape of what is known and unknown about the suitability of various methods for approaching these problems.

The agenda is given in Appendix B. First, participants described the mission area each was supporting. The slides used in this briefing are provided as Appendix C. This was followed by a conversation about the common features with the goal to define a decision problem as generally as possible so that it represents all the mission areas. Next, in the "Technology Transfer" session, experts summarized relevant findings and techniques in their fields that might be unfamiliar to participants from other fields. Finally, on the second day, we continued conversations that were triggered by the first-day sessions, consolidated that information, and then formulated a general asset allocation problem and the supporting information content.

1. General Asset Allocation Problem

It is possible to produce a single formulation for the optimization of asset allocation such that it is representative of every mission area discussed. Several distinct objectives may be represented, and there are algorithms that may solve these problems, usually heuristically. The curse of dimensionality is relevant in this problem, especially due to multiple time-steps, multiple assets with distinct capabilities, multiple targets, and the potentially large geographic area over which the assets may be allocated. This formulation is offered in the Section II.

We will use the term “Blue” to refer generally to the forces combating the threat and, unless otherwise specified, will assume that they are coordinated and therefore operating as a single decision-making entity with multiple assets. We will use the term “Red” to refer to the adversary, which will generally have multiple assets (vessels, unless otherwise specified). In some cases, Red assets are coordinated, and in other cases they are not.

Strategic behavior—i.e., an adversary who intelligently anticipates Blue’s decision-making process—substantially complicates the decision problem. The participants determined that strategic behavior is not a critical element of the mission areas at this point, but that if it becomes critical, it will need to be addressed with a fundamentally different approach in which the information generation and the optimization algorithms cannot be separated.

2. Information Required

Three major categories of environmental information are exploited in the mission areas addressed:

- **The natural environment**: i.e., Meteorology and Oceanography (METOC) and topography and bathymetry.
- **Capabilities**: i.e., the ability of Blue (and potentially Red) assets to achieve their objectives; e.g., the probability of detection; the speed of travel.
- **Target positions**.

The asset allocation problem benefits from the fact that these three types of information may be summarized as the probability of detection (or interdiction) as a function of Blue’s asset positions. This greatly simplifies the optimization problem and the information-exchange requirements between the environmental information production organization and the decision-making function, whether human or algorithm.

3. Implementation Challenges

In many of the mission areas, a human will make decisions regarding the asset allocation. This raises several challenges, including providing decision support that the commander will be willing to use.

Presentation of high-dimensional information in a form that human users can readily understand is very challenging. For example, the probability of detecting a target is a function of, at a minimum, the detector's position; the target's position; and the environment. Users are familiar with map-based representations; how should the probability of detection be displayed? The convention has been to present a map showing at each point the probability of detecting a target given that the target is equally likely to be in any position (uniform target distribution), conditional on the detection asset being at each point.

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II. GENERAL MISSION FORMULATION

Slides summarizing each mission area are provided in Appendix C. The mission areas described may be broken down into two major categories:

- allocation of multiple assets over position and time, for surveillance (search and detection) and targeting (interdiction/prosecution); and
- routing for a single asset for force protection and fleet safety.

Each category also includes missions that do not involve an adversary. For example, the asset-allocation category includes ocean sensing with unmanned gliders. Their task is sampling/sensing to optimize a measure of improvement in information (e.g., bathymetry). The routing category includes not just routing ships to minimize the likelihood of attack (e.g., from a fleet of small boats [the asymmetric adversary]), but also routing ships to minimize environmental risk (e.g., exposure to airborne radioactive material). Because we have excluded the problem of strategic behavior by the adversary, these adversary-free mission areas may be represented and solved using the same basic problem structure.

Table 1. Examples of mission areas by inclusion of an adversary or target and by framing as asset-allocation or routing problem.

	Asset Allocation	Routing
Adversary	Counter-piracy Counter drug traffickers Anti-submarine warfare (ASW) multistatic networks	Small boats avoidance Piracy avoidance
No Adversary	Ocean sensing with sonabuoys or unmanned maritime vehicles (UMVs) Adaptive ocean sampling	Environmental risk avoidance

The decisions are where to position assets $i = 1,\ldots,n$ over a planning horizon $t = 0,\ldots,T$ ().[1] The position of asset i at time t is $x_i(t)$, with $\mathbf{x}$ giving the positions of all n assets through time T and the objective is:

$$\max_{\mathbf{x}} f(\mathbf{x}),$$

where $f(\mathbf{x})$ is some function that captures uncertainty in the achievement of an underlying objective, cost, or fitness function (different research communities use different terms), denoted $g(\mathbf{x})$. The information state is denoted as ϕ, and so one possible formulation of the objective, accounting for uncertainty, is $f(\mathbf{x}) = E\left[g(\mathbf{x})\middle|\phi\right]$. For detection and interdiction problems, $g(\mathbf{x})$ must be a function of target positions.

[1] For convenience, we are denoting the discrete-time problem, which is very common, but not universal, in formulations of these problems.

For many detection and interdiction formulations, however, $f(\mathbf{x})$ is not necessarily an expectation, e.g., it could be $\max_{\mathbf{x}} P(\text{intercepting at least one target})$ or $\min_{\mathbf{x}}\left(\max_{j}\left(1-P\left(\text{probability of detecting target } j|\phi\right)\right)\right)$, i.e., minimize the worst (over all targets) nondetection probability, as in Royset's formulation, described below.

This formulation is general enough to represent go:no-go decisions, or decisions about when and where to operate to avoid severe weather. The function $g(\mathbf{x})$ could be:

- an indicator of whether the asset encounters dangerous weather (0 if it does, 1 if it does not, to preserve the maximization convention);
- an information-content measure associated with a sampling task;
- the number of targets detected (for a detection problem); or
- an indicator of whether a target is intercepted (1 if intercepted, 0 otherwise).

A. INFORMATION DECOMPOSITION FOR MISSIONS WITH AN ADVERSARY

Although the objective function differs by mission area, the information state may be decomposed for missions with unknown target positions. For each mission area, the objective is a function of the probability distribution of the target position(s) and Blue asset capability as a function of position. The information state ϕ describes target position(s) and Blue asset capability as a function of asset (and perhaps target) positions, where $y_j(t)$ is the position of target j at time t and $\mathbf{y}$ gives the positions of all m targets through time T. Moreover, the information state may be summarized as the probability of target detection (interdiction), conditioned only on the Blue asset position, which is a decision variable, and not conditioned on target position.

$$P\left(i \text{ detects } j \text{ at time } t|x_i(t),\phi\right)=\sum_{y}\underbrace{P\left(i \text{ detects } j|x_i(t),y_j(t)=y,\phi\right)}_{\substack{\text{conditional detection probability, a function}\\ \text{of asset capability, as a function of asset and}\\ \text{target positions, reflecting relative positions}\\ \text{and natural environment (sensor performance)}}}\times\underbrace{P\left(y_j(t)=y|\phi\right)}_{\text{target location distribution}} \quad (1)$$

The above formulation is a critical conclusion. For detection (interdiction) missions, uncertainty about target position and asset capability may be combined, and the information state expressed as the unconditioned probability of target detection (or interdiction), given asset position(s). The assumption that target behavior is random (not intelligent) implies that target positions, $\mathbf{y}$, are not a function of asset positions, $\mathbf{x}$, though they may be a function of other factors in the environment, such as meteorological and oceanographic conditions (METOC). This allows information about the environment to be analyzed independently of the optimization problem, given some assumptions about the optimization time horizon and the importance or time-scale of strategic behavior by the targets.

The information relevant to the objective functions may be summarized as the unconditioned probability of a target detection as a function of asset positions, i.e., the left-hand expression in Equation (1) above. Moreover, if all targets may be treated as identical in value (but not necessarily in behavior or distribution), the information state may be summarized over all targets, i.e.,

$$P\left(i \text{ detects any target at time } t \middle| x_i(t), \phi\right) = 1 - \prod_{j=1}^{m} P\left(i \text{ does not detect } j \middle| x_i(t), \phi\right)$$

In this case, the information may be represented as a simple function of asset position, and therefore plotted on a map, which matches the convention for most performance surfaces and many other decision support tools for maritime operators.

An adversary who intelligently anticipates Blue's decision process substantially complicates the decision problem in a way that we believe will reduce the performance human judgmental asset allocation solutions and also makes most of the work on optimization algorithms inapplicable.

It should be noted that various approaches currently being pursued might capture intelligent behavior by the adversary, such as exploiting METOC forecasts and seeking to hide in areas where they anticipate that Blue's capabilities will be reduced. They do not, however, capture a strategic interaction in which the adversary anticipates the way Blue will make its decisions.

III. OPTIMIZATION

There is a substantial body of research on optimization algorithms to support decisions of this type. The dimensionality of the problem is limiting, however, especially in the case of coordinating multiple assets with distinct characteristics. For example, in a search problem with N_S searchers (with distinct sensors), N_T targets, N_P possible positions, N_E possible environmental conditions, and T time-steps in the horizon, there are $\left(N_S N_T N_P N_E\right)^T$ possible scenarios to be evaluated. Moreover, the dimensionality of these problems is increasing, with the addition of more, often unmanned, search assets and the increasing importance of asymmetric threats, constituting multiple small targets.

A further challenge is coordinating the interacting problems of detection and interdiction. In several mission areas, aircraft are used in detection, while interdiction is almost exclusively by vessels. Therefore, the time-scales of motion are very different.

A. APPROACHES TO OPTIMIZING DETECTION AND INTERDICTION

Two experts in optimization algorithms for detection and interdiction problems shared with us accessible summaries of the state of models and solution algorithms for problems of this type.

Johannes Royset, in his presentation titled "Models for Optimal Routing of Searchers against Random Targets," described the curse of dimensionality in the problem with multiple targets, multiple search assets, and with moving targets. He formulates a discrete-time, discrete-space (area of interest is partitioned into cells) problem in which search asset routes are constrained (assets cannot instantaneously move to any cell in the area of interest). There are multiple targets and multiple searchers, which may have different capabilities. In addition, in his formulation, the optimizer considers the cost of false detection (i.e., in addition to adversaries, there are neutral entities that may be detected and mistaken for adversaries). This formulation is a convex, nonlinear integer program, which is NP-hard.[2] However, he proposes cutting-plane algorithms that can solve the problem to near-optimality in a reasonable amount of time by restricting the horizon to the time until the next detection. Optimizing only until next detection makes the problem tractable; this becomes less optimal when there are more false positives.

It should be noted that if false detections are important, this would also complicate the information requirement, described above. In particular, the probability of detection, conditional on a target being present, implies a signal threshold for detection to be triggered. This threshold is presumably set such that false detections do not interfere with the mission. However, having the threshold-setting decision made independently of the rest of the optimization may be far from optimal. For example, it may be optimal for the threshold to vary based on what is known about the target density and/or the relative

[2] A problem is NP-hard if there is no algorithm that can solve the problem in a processing time or number of operations that is a polynomial function of the size of the problem; see Tovey (2002) Section 1 for a fairly accessible definition.

distribution of targets and neutral entities. In this case, additional information might be required: an additional dimension, reflecting the signal-detection threshold and/or the probability of false positive including detecting a neutral, as a function of asset position and the information state.

In continuous space and time (which is rare; see the Literature Review section), the formulation changes. The problem may be reasonably solved, however, by parameter-distributed optimal control algorithms or direct methods-based discretization of time and space. As illustrated in Figure 1, these models are appropriate for "close control" of searchers, i.e., the solution produces precise searcher paths. It was noted that optimized paths might not be realistic movement paths, but Royset stated that it is relatively straightforward to constrain the continuous-optimizer to produce more realistic paths. Even if realistic, however, it is unlikely that precise search paths would be implementable by, for example, a surface vessel or piloted aircraft. This kind of optimization would probably be most applicable to an automated searcher, e.g., control of an unmanned aerial or undersea vehicle.

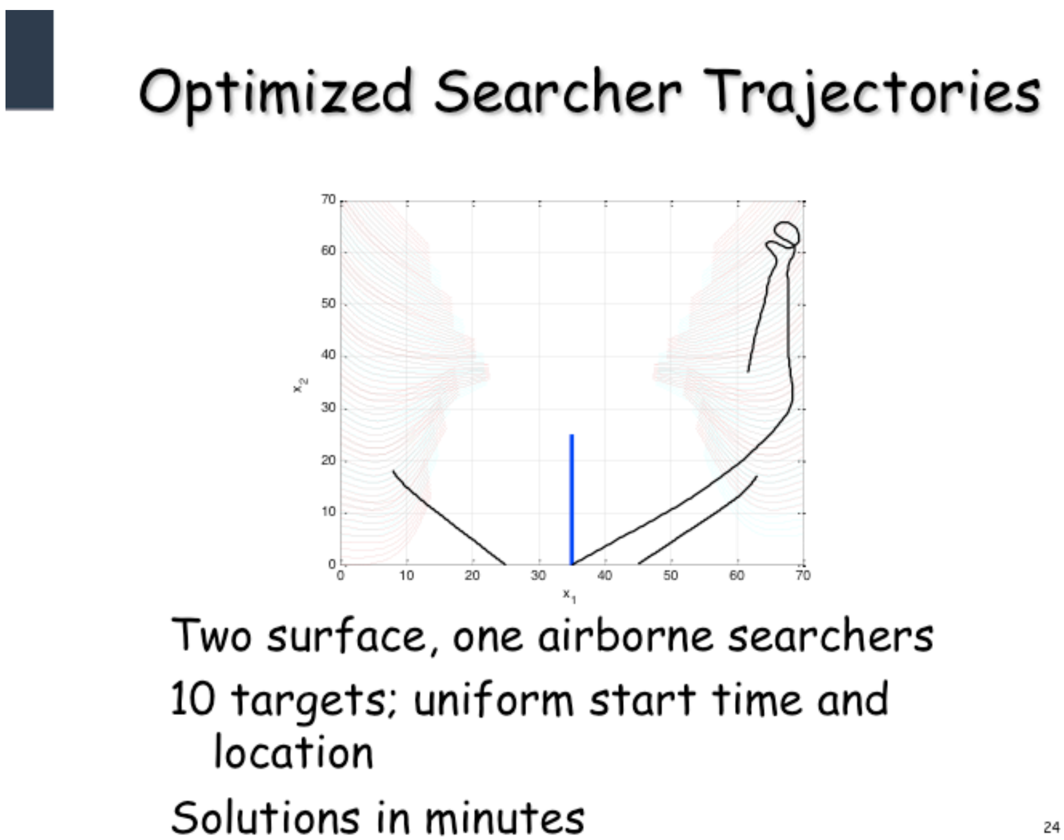

Figure 1. Example of continuous-time optimal search paths. The blue line represents a high-value asset that the adversary wishes to attack. Red adversary paths approach from each side. Optimal searcher paths (two surface, one airborne) are shown in black. From Royset (2012, March).

Both the discrete and continuous-time optimization models assume a conditionally deterministic or Markovian model of target motion. Conditionally deterministic motion implies that if you knew precisely where the target was at a given point in time, you would know precisely where it would go in the future). This is a special case of Markovian motion in which each period's position is probabilistic, but the distribution is conditional only on the in target's state in the prior period. Such a model contains more information than a set of probability density maps, and this information is exploited in the algorithm. This implies that there is a need for target models that can be used in this type of model.

Krishna Pattipati, in his presentation titled "Dynamic Resource Management Algorithms," showed a schematic (see Figure 2) of the general problem, to include the distinction between detection and interdiction assets. He described several approximation strategies used to overcome the curse of dimensionality, and showed examples from his previous work. The mission areas include tactical asset allocation for surveillance, asset allocation for the combined interdiction and detection problem, command-level planning and allocation of resources at the task-force (multi-asset) level, and asset routing.

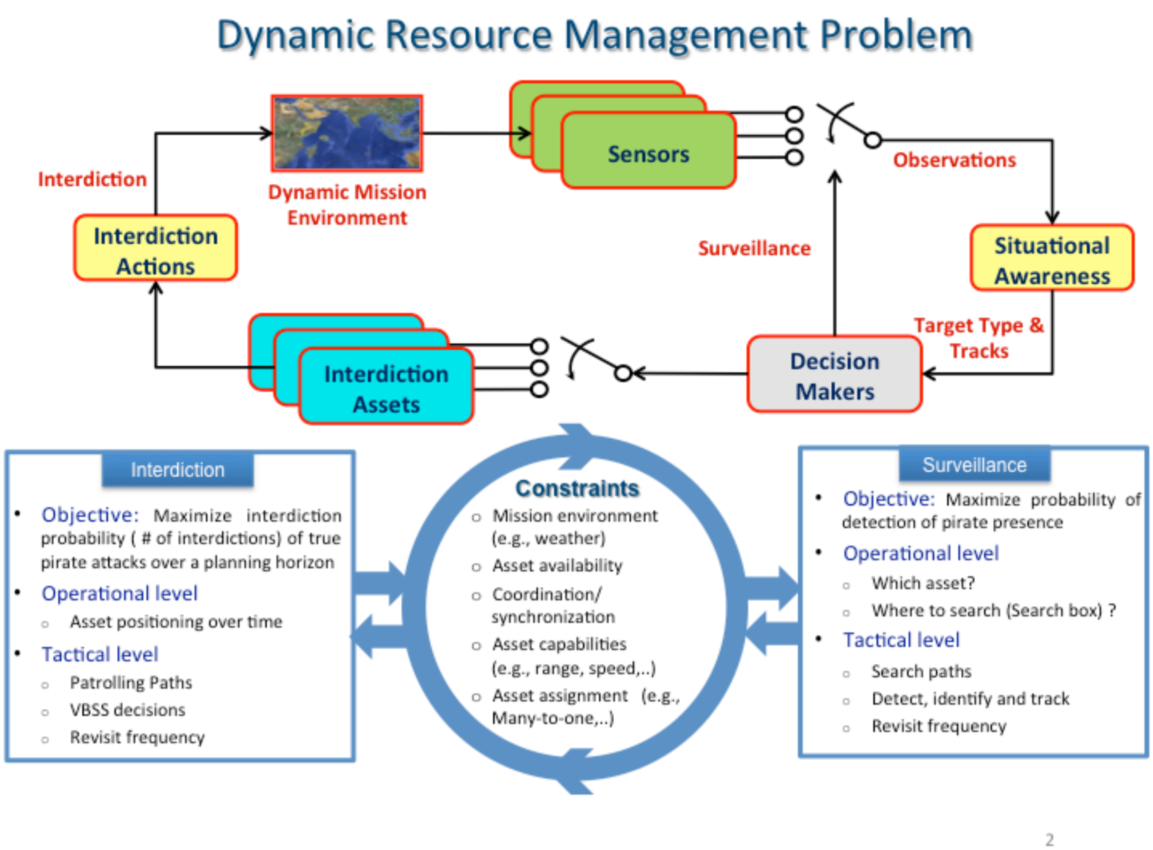

Figure 2. Schematic of general combined interdiction/detection problem. Pattipati et al. (2012)

In addition, he described approaches to modeling the information state, specifically Hidden Markov Models (HMMs), in which the evolution of the variables that will affect the objective function is Markovian, but information about these variables is observed with error. HMMs provide a structure for this type of situation and methods for estimating the parameters of process for the evolution of the underlying variables as well as the "emission" process that produces observations. The resulting HMM can support dynamic optimization algorithms.

Because both constraints (e.g., path constraints) and the objective function (e.g., probability of interdicting a smuggler before he reaches his destination) are functions of asset positions and the state of information at multiple periods, optimization methods (and many heuristics) require a model of the relationships among probability distributions over time. Both Royset (2012) and Pattipati et al. (2012) make the assumption that target motion is represented by a conditionally deterministic or Markovian model. However, the only existing target information product—the Pirate Attack Risk Surface (PARS) (see Hansen et al., 2011)—provides forecasts of instantaneous distributions of target position. This suggests the need for developing model-reduction techniques that produce models that have the Markovian property and can be used to support these optimization algorithms.

B. LITERATURE REVIEW

The differences among problems and the vast array of classes of algorithm that may be used to solve the general problem suggested that a deeper literature review would be valuable. This a valuable reference for researchers from the METOC community who are often familiar with techniques like genetic algorithms. Genetic algorithms may be applied to a wide range of problems, but do not exploit special features of any specific problem. Instead, they search the space of possible solutions, and may come up with good, but not necessarily optimal, solutions if given enough time.

The search theory literature combines some of the aspects of the information stage with the optimization of asset allocation stage. A highly-cited survey of the search theory literature is provided in Benkoski, Monticino & Weisinger (1991). Their survey focuses on the allocation of the search effort, allows uncertainty in the inspections, and a passive or evasive target. Targets can be stationary, or moving, where their movement is conditionally deterministic or according to a Markovian process.

Much of the research in this area relates to specific mission contexts that not discussed at the workshop, such as search and rescue (Abi-Zeid, Nilo & Lamontagne, 2011) and the tracking decisions and coordination of satellite-based sensors searching for maritime targets (Berry, Pontecorvo & Fogg, 2003). The remainder of this section briefly reviews the literature for various mission types in terms of specific challenges and modeling choices most relevant to the targeting missions discussed at the workshop.

1. Search and Interdiction

While the search problem is itself quite challenging, optimizing for both search and interdiction simultaneously adds to the challenge. In many missions, such as counter-drug trafficking, the aircraft are used to search while vessels are used to interdict. Integrating them creates potential incompatibility in asset motion assumptions, grid resolution, etc. Kress, Royset & Rozen (2010) provide a stochastic-dynamic formulation of a search and interdiction problem using a single searcher and a single interdictor. The problem is hard, and they solve it with a heuristic that involves searching the cell with the highest ratio of probability of a target to time required to get there. An et al. (2012) exploit special features of the counter-piracy objective function to decompose the problem, optimizing interdiction first, and then optimizing the detection problem given the interdiction solution.

2. Number of Searchers and Targets

This section discusses the different ways that researchers have developed for dealing with different numbers of searchers and targets. Dell et al. (1996) formulate a multi-searcher (single target) problem and develop heuristic approaches to its solution, testing them for up to three searchers and up to 49 cells. Royset and Sato (2010) model multiple searchers and multiple targets, coordinating searchers, in part, by including constraints to limit the number of searchers that can occupy the same cell.

Chung, Kress & Royset (2009) formulate the problem of multiple searchers that should be closely coordinated—specifically, they are motivated by coordinating unmanned aerial searchers—updating the probabilistic representation of the likelihood of the locations and identities of targets. In related work, Chung and Burdick (2008), in a similar model, consider information sharing among multiple searchers with distributed planning (each searcher's plan is selected independently) as a way to achieve coordination.

3. Discretization of Space and Time

Most of the literature assumes a discrete set of fixed, equally sized cells in two-dimensional space, and the optimization algorithms operate in discrete time (e.g., Brown et al., 2011; Brown, 1980; Dell et al., 1996; Chung et al., 2009). In this section, we discuss papers that differ or improve on this standard. Sato and Royset (2010), for example, use discrete cells, but allow the searcher to move in three-dimensional airspace.

Many papers assume equal, rectangular sized cells for simplicity, but the methods can be extended to arbitrary and varying cell sizes, especially if there is no searcher path constraint. Stone (1979) addresses all combinations of continuous and discrete time and space, with a single target and searcher. Dambreville and Le Cadre (2002) model and propose an algorithm for solving a continuous-space problem.

Wilson, Szechtman & Atkinson (2011) allow for arbitrary cell shapes in a detection problem with stationary targets. Abi-Zeid et al. (2011) address the problem of defining and assigning multiple, non-overlapping, different-sized, rectangular subareas to search assets for a search-and-rescue (stationary target) application.

4. Target Information Models

Benkoski et al. (1991) observe that, to the date of his review, most authors model target motion as conditionally deterministic (i.e., if the target's current position were known, its future position would be known with certainty) or as Markovian (i.e., given the target's current state, often identical with its position, the probability distribution of its future motion is known). It remains true that many search researchers assume conditionally deterministic or Markovian target motion, generally with very simple motion patterns (e.g., Brown, 1980; Kress et al., 2010; Dell et al., 1996; Dambreville & Le Cadre, 2002; Berry et al., 2003).

5. Intelligent Agents

In the mission contexts discussed at the workshops, it is generally agreed that target behavior may be modeled as random, rather than intelligent. There is, however, some existing literature on related problems, with targets modeled as intelligent agents. Eagle and Washburn (1991) model a single-target, single-searcher, multi-move game in which both target and (of course) searcher behave intelligently. Most recently, Brown et al. (2011) model the problem of using a set of non-homogenous search assets to detect submarines attempting to attack a stationary position. The attacking submarines choose a path intelligently, minimizing their probability of detection by the search assets; the problem is formulated such that an optimal search plan may be found using algorithms that solve a mixed integer program. The field of robotics has generated much research on pursuit-evasion games, where the target is actively avoiding the searchers. Chung, Hollinger & Isler (2011) survey this research taxonomy.

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IV. ENVIRONMENTAL INFORMATION

The primary community that generates environmental information for maritime targeting problems is the METOC community. As illustrated in Figure 3, the U.S. Navy METOC program's operational concept is based on the Battlespace on Demand (BonD) pyramid, with four tiers:

- Tier 0: the data layer, i.e., raw environmental data;
- Tier 1: the environment layer, i.e., a description of the past, present, or predicted environment, including oceans, atmosphere, topography, and bathymetry;
- Tier 2: the performance layer, which describes the impact of the environment on capabilities, including sensors and platforms; and
- Tier 3: the decision layer, which provides actionable information including risk assessments to support tactical, operational, and strategic decisions.

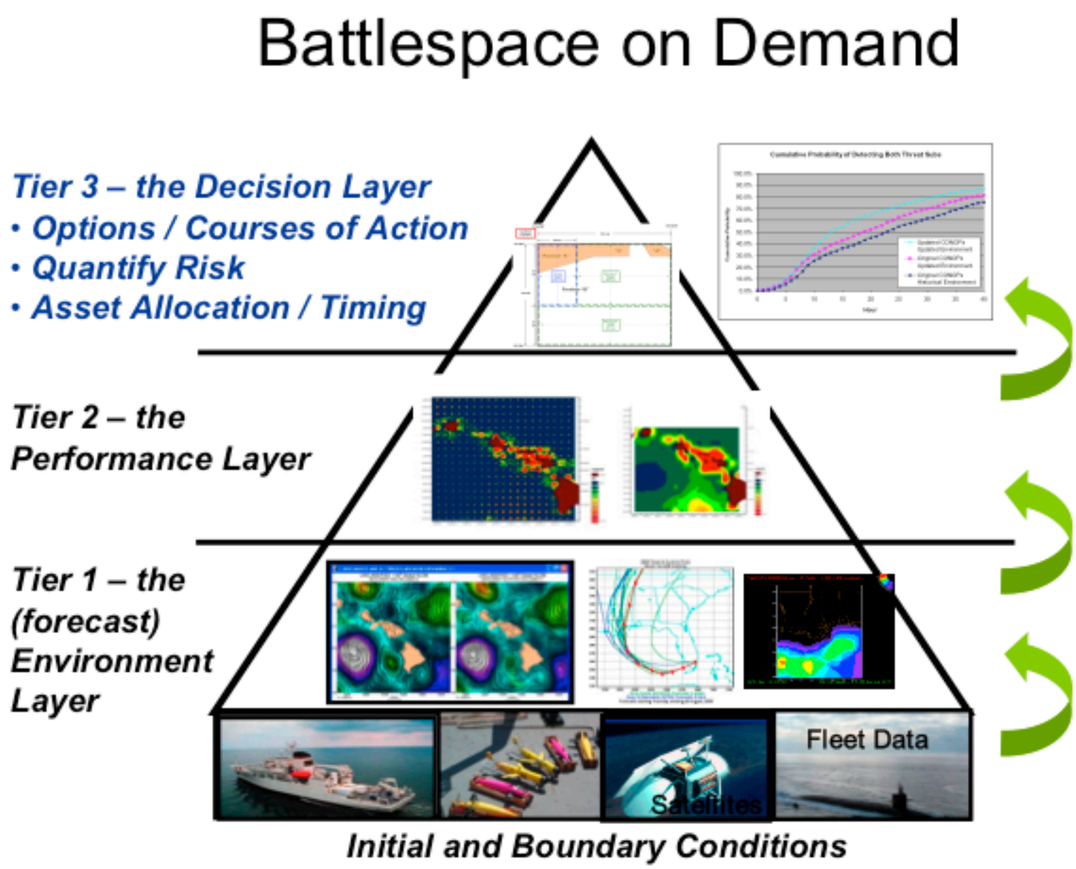

Figure 3. The U.S. Navy's Battlespace on Demand (BonD) pyramid.

The definition of Tier 3 is still a subject of debate; at the workshop, there was a long debate about whether optimization results may be considered a Tier 3 product or whether they must be considered outside the BonD pyramid. Tier 3 support is still almost always provided by the human forecaster, rather than through an operational informational product. The Pirate Attack Risk Surface, described in Hansen et al. (2011) and at the workshop by Jim Hansen (see Appendix C) is an operational Tier 3 product that estimates the risk of pirate attacks as a function of environmental information.

In recent years, many Tier 2 products have been developed, such as the acoustic performance surface, described by Steve Dennis (see Appendix C) and the radar, communications, and sensor performance surfaces described by Tracy Haack (see Appendix C). Performance of radar and sonar sensors and communications assets is highly dependent on environmental conditions surrounding emitting and receiving assets and any target. Radar and communications use electromagnetic waves traveling through the atmosphere, while sonar depends on acoustic waves propagating through the oceans. Wave propagation, however, is generally very dependent on temperature and pressure differentials and may be channeled into layers or ducts, such that signal transmission may be great in one direction or vertical layer and small in others. In addition, both are susceptible to interference by other waves.

The estimation of the performance is a very computationally complex problem. For example, for a 139×114 grid at a 5-kilometer km resolution, with 40 levels and an aircraft flying at 500 meters, a single forecast lead time, single radial, single sensor, single target calculation for the entire domain would take approximately 5 minutes on a single processer. The processing time scales linearly with number of forecast leads, number of radials, and number of sensors. The processing scales nonlinearly with number of flight levels (as a function of altitude). The cost of additional targets is minimal. However, the problem scales very well across processors. The ability to provide performance surfaces to commanders is currently limited by not just by computational capacity but also by available bandwidth for communicating relevant information to ships afloat.

It is also highly dependent on the quality of environmental information. Using higher-resolution environmental information increases the computational demand, but also increases the accuracy. The computational burden and the informational requirements both constrain the generation of sensor and communications performance surfaces for the U.S. Navy to operational centers at the Naval Oceanography Command (NAVO) and Fleet Numerical Weather Center (FNMOC).

For many missions, the optimization must be conducted locally to the decision makers, e.g., on board a deployed vessel, or even aboard an autonomous glider. This creates a need for physical separation between the asset capability modeling and the optimization. The optimizers must reach back periodically to get asset performance information. A schematic representing the combined information-optimizer system as applied to counter-piracy operations, using the PARS, is shown in Figure 4.

In addition to the physical separation, the optimizer and the performance information may be generated at different time-scales. Performance surfaces take hours to produce, while the optimizer may be run at more frequent intervals, especially when new, relevant information is received, e.g., with respect to target positions (in the case of the counter-smuggling mission at the Joint Interagency Task Force-South [JIATF-S]) or sensor-generated input (in the case of ocean-sensing gliders). In some cases, this implies a need for a local, approximate update of the asset performance information, as depicted in the blue box labeled "Local" in Figure 4. Local updating for both asset performance and target position will be discussed further below.

A very important piece that is missing from the sonar performance (for ASW) surfaces is the spatial-temporal distribution of target presence probabilities. Currently, the surfaces are based on the assumption that the target distribution is uniform, which is clearly inaccurate, but provides a starting point.

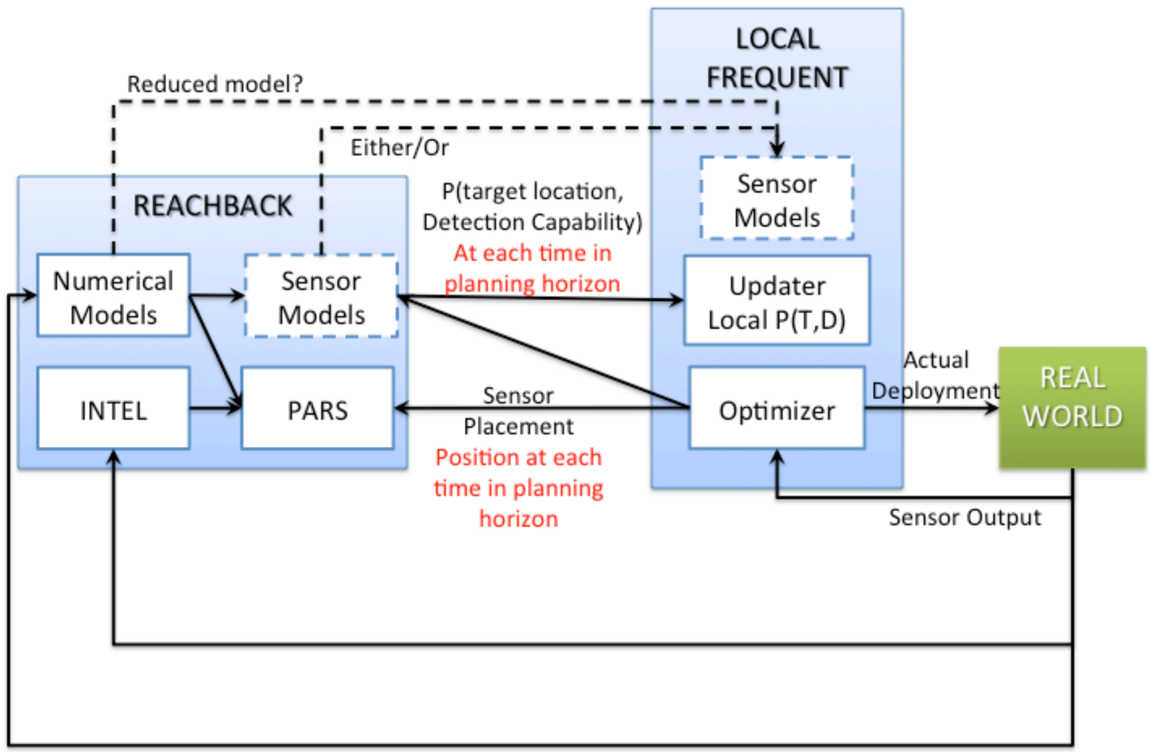

Figure 4. Schematic of combined information-optimizer system, for the counter-piracy mission using the Pirate Attack Risk Surface (PARS). This figure was produced manually the workshop participants on the white board during the final session of the workshop and recorded by Diego Fernando Martinez Ayala.

Limitations on the bandwidth for transmitting information to ships afloat, and issues in matching the information to optimization inputs indicate that there is a need for systematic thinking about model reduction.

One exception to the general rule that researchers working to develop better informational tools are separated from researchers working on optimization is the work at the NATO Undersea Research Centre (NURC), represented at the workshop by Raffaele Grasso. For detection (interdiction) missions, uncertainty about target position and asset capability may be combined, and the information state expressed as the unconditioned probability of target detection (interdiction), given asset positions. This allows information about the environment to be analyzed independently of the optimization problem, given some assumptions about the optimization time horizon and the importance or time-scale of strategic behavior by the targets.

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V. IMPLEMENTATION

A. HUMAN FACTORS

For some of the mission areas, e.g., path planning for unpiloted gliders, the goal is to fully automate, and even distribute, the asset allocation decision. In many mission areas, however, certainly including the counter-piracy, counter-smuggling, and small boat problems, automation of these decisions is not anticipated. Rather, the goal is to support commanders' judgmental decisions by recommending (optimized) courses of action and alerting the decision makers to informational innovations that call for a change in the course of action (reoptimization).

Larry Shattuck presented the group with a discussion of the human dimension of the problem, specifically organized around his Dynamic model of Situated Cognition (Shattuck & Miller, 2006) and shown in Figure 5, which classifies the various sources of error, from the sensor side (left), through the presentation of information to the user, and the user's perception and processing of the information (right). The human interface is the communication of the system designer's intent. He recommends making it easy to evaluate the current state of the system.

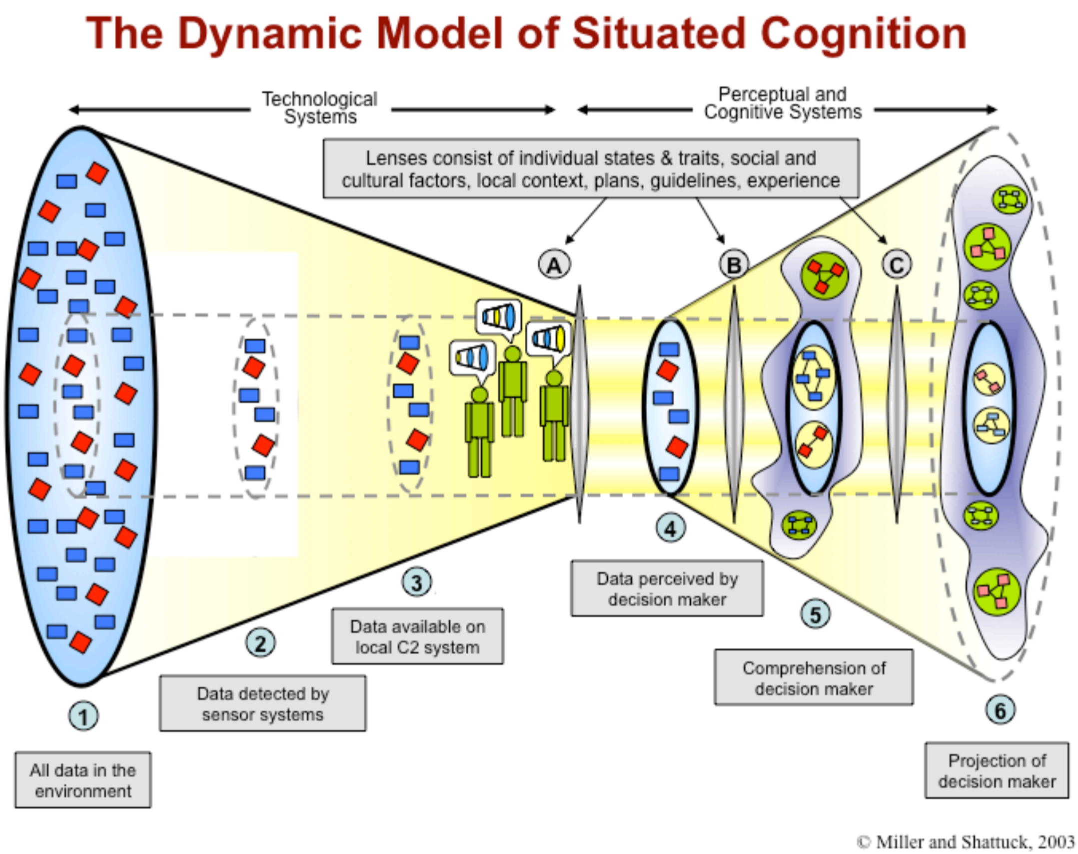

Figure 5. The lens model, from Shattuck (2012).

In addition, he stated that in his experience, users do not like an automated agent, i.e., an optimizer. He recommends keeping the operator in control and in the loop, and making it obvious what the system is doing.

This talk highlighted several human-factors challenges are relevant to this problem, as detailed below.

1. High-Dimensional Information

Presentation of high-dimensional information in a form that human users can readily understand is very challenging. For example, the probability of detecting a target is a function of, at a minimum, the detector's position; the target's position; and the environment. For undersea applications, the detector's position and the target's position each have three dimensions. The problem is further complicated when the detection system is made up of multiple interacting assets; e.g., when there is at least one active (emitting) asset and at least one other receiving asset; or the signal is a composite of multiple detectors' inputs.

Users are familiar with map-based representations. The convention has been to present a map showing at each point the probability of detecting a target, given that the target is equally likely to be in any position (uniform target distribution), conditional on the detection asset being at each point. Shattuck recommends the reference "Display and Interface Design: Subtle Science, Exact Art" by Bennett and Flach (2011). Dave Kleinman pointed out that this implies that cognitive task analysis is a necessary step in designing informational- or optimization-based decision support systems.

2. User Acceptability

In many of the mission areas, a human will make decisions regarding the asset allocation. This raises several challenges, including providing recommended courses of action that the commander will be willing to use. Jim Hansen's experience is that users are uninterested in a decision support tool if they already have a way to make that decision. They were receptive to the PARS because they did not have another source of the information they perceive is contained in PARS. By contrast, the operators at JIATFS do have a process for making decisions regarding the allocation of counter-piracy assets.

A key challenge to introducing an optimizer into this process, then, is to provide results that are usable and appealing enough to overcome the resistance to change and loss of control.

As Shattuck pointed out, in order to design a decision support system that is used (rather than following the "vaunted introduction" followed by "veiled discard" trap), it is essential to work with the users in designing the system.

Krishna Pattipati and colleagues have addressed this in several ways (An et al., 2012). First, they define the decision variables to match the way asset allocations are implemented. In particular, rather than producing an hour-by-hour or minute-by-minute path, the optimizer generates a search box that matches the U.S. Navy's convention of assigning each vessel or aircraft to a patrol area, usually rectangular, for a period of hours or a day. In addition, the optimizer produces three alternative courses-of-action so that if one of these is not practical for reasons not captured by the constraints in the optimization, there is another alternative that is nearly optimal that he can select. This also gives the user a greater sense of control, even while he takes advantage of the optimizer's solution.

Raffale Grasso and his colleagues have addressed this challenge in their design of a general-purpose maritime operation support system. As described at the workshop, their system provides users with an efficient frontier of non-dominated solutions, each optimal for a given relative weighting of multiple objectives. This approach also provides multiple good options and a sense of control to the user.

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VI. RECOMMENDATIONS

One of the most important accomplishments was simply that we brought together the researchers working on optimization with those working to generate the information that the optimizers anticipate using in their algorithms. This is a surprisingly rare occurrence. It is nearly universal for the optimization community to assume that relevant environmental information is available, often in a highly simplified form matched to the optimization algorithm, at matching variables, resolution and with perfect calibration. Similarly, it is common for the information-generation (principally, METOC) community to engage in a one-way relationship in which they provide a product and the responsibility for understanding and extracting value from the information falls on the users.

This workshop led to the exchange of some important ideas, such as some of the insights from the human factors literature that highlight the importance of displaying sensor performance information in a user-intuitive format. In addition, researchers from the information (METOC) side were introduced to algorithms that are tailored to the details of this problem, contrasting with general, "brute force" approaches such as genetic algorithms. On the other hand, optimizers were exposed to the challenges and magnitude of the sensor-performance prediction problem and the relative lack of useful models of target position.

The most important conclusions were that we can formulate a general version of this problem, and that approximate dynamic programming algorithms are the most amenable class of algorithms to the solution. We can also summarize the relevant information state as the probability of detecting (interdicting) a target conditional only on the information state and the position of Blue assets (except when false detections or strategic behavior are important). This allows the separation of the information-production operation from the optimization and implementation, with feedback that may occur relatively infrequently. This also implies that local approximate updating may be needed for some missions.

We identified a number of important open questions, whose answers can guide future research efforts in all areas:

- How good does radar or sonar surface have to be? In other words, can we determine a level of accuracy above which improvements in accuracy or resolution will not substantially affect the optimal allocation of assets?
- How complex a target behavior model is necessary? This boils down to a question of how good the target distribution prediction is, and can we build a simple model, amenable to quick updates to incorporate new information, that produces optimal asset allocation solutions that are similar to those produced by more detailed and computationally demanding models.
- How much value do you give up in optimization by using a receding horizon feedback, rather than a closed-loop complete optimization?

- How can you automatically provide, together with a solution resulting from an optimization, an explanation of the solution proposed, such that the user can, at some level, understand why the system is making a given recommendation?
- Can we develop good methods for reducing environmental and target model size such that the reduced-scale models support optimization algorithms and rapid, local updating for incorporating new information?
- Under what circumstances can we decompose the optimization problem by assigning targets to assets?

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APPENDIX A. LIST OF ATTENDEES

Participant Bios
Targeting an Asymmetric Maritime Threat
March 13-14, 2012
Naval Postgraduate School
Monterey, CA

Michael Atkinson has been an Assistant Professor in the Operations Research Department of the Naval Postgraduate School since May of 2009. He attended graduate school at Stanford University and received his Ph.D. in Computational and Mathematical Engineering. Dr. Atkinson is interested in applied probability, stochastic processes, and using mathematical models to gain insight into the challenges facing military operations, homeland-security, and healthcare. His research has included projects that examine the interdiction of terrorists, popular support for insurgencies, patrolling under uncertainty, detection of drug smugglers, and blood transfusion policies. Dr. Atkinson teaches Computation and Decision Analysis courses at NPS. *mpatkins@nps.edu*

Dr. **Brian Bourgeois** completed his Ph.D. in Electrical Engineering at Tulane University in New Orleans, Louisiana in 1991. He retired as a Captain from the U.S. Naval Reserve in 2008, after 28 years of active and reserve service. He is presently head of code 7444 in the Naval Research Laboratory detachment located at Stennis Space Center, Mississippi. His work there has involved the development of unmanned maritime vehicles and sensor systems, and underwater navigation and communication systems for UUV teams. His recent research interests have been in the development of advanced mission planning and management systems for UUV teams. *brian.bourgeois @nrlssc.navy.mil*

Dr. **Emanuel Coelho** was a naval officer in the Portuguese Navy, worked as a scientist at the NATO Undersea Research Center, and is now a Professor-Research at the University of New Orleans, resident at the Naval Research Laboratory at Stennis Space Center. He has a Ph.D. in Physical Oceanography from the Naval Postgraduate School in 1994, and was recognized as a Doctor in Physics by Lisbon University in 1996. His present research focus is on developing operational oceanography products using stochastic forecasting methods, nonlinear filtering theory, and control theory, which includes environmental Adaptive Decision and Risk Management. Dr. Coelho publication records include more than 75 articles in journals, proceedings, books, and technical reports. He is acting as reviewer for several major scientific journals in ocean sciences. *emanuel.coelho.ctr.po@nrlssc.navy.mil*

Steven M. Dennis is a physicist with 10 years' experience in underwater acoustics at NRL. He recently completed sea data comparison validation of uBand, and is currently heading the V&V effort on the NAVO Acoustic Performance Surface project. Additionally, he is acting technical lead on proposed changes to operational performance surface development. Other work in underwater acoustics includes development and testing of search path planning algorithms. Mr. Dennis has B.S. and M.S. degrees in physics. *Steven.dennis@nrlssc.navy.mil*

Raffaele Grasso has a M.Eng. in Telecommunication from the University of Pisa, Italy, and a Ph.D. in remote sensing from the University of Florence, Italy. He has been a scientist at the NATO Undersea Research Centre (NURC), La Spezia, Italy, since 2006. His main research interests include statistical signal and image processing, machine learning, remote sensing, target detection, maritime surveillance systems and decision support systems for operation planning. *grasso@nurc.nato.int*

Ms. **Tracy Haack** has been on the Mesoscale Modeling team and Prediction Systems Branch of the Naval Research Laboratory's Marine Meteorology Division for over 20 years. She began employment at NRL in 1990, after graduating with an M.S. and B.S. from The Pennsylvania State University. Working initially on the marine boundary layer and air-sea coupled processes, Ms. Haack's interests have evolved toward applied studies of numerical weather prediction over the last 10 years to investigate refractivity and atmospheric ducting and its impact on electromagnetic propagation and radar, communication and sensor systems. Her work with NPS and SSC-Pacific led to a real-time demonstration of radar performance surface products for RIMPAC-08 mission operations. *Tracy.haack@nrlmry.navy.mil*

Dr. **Jim Hansen** is the lead scientist of the Naval Research Laboratory Probabilistic Prediction Research Office (Code 7504) in the Marine Meteorology Division and is the acting branch head for the Meteorological Applications Development Branch. Prior to joining NRL in 2006, he was a professor of atmospheric science in the Earth Atmospheric and Planetary Sciences Department at the Massachusetts Institute of Technology. He received his Ph.D. in Atmospheric, Oceanic, and Planetary Physics at the University of Oxford, where he was a Rhodes Scholar. His B.S. and M.S. were both obtained from the University of Colorado, Boulder in Aerospace Engineering. Dr. Hansen's research interests are wide-ranging, but are focused on the estimation and communication of uncertainty information for improved scientific understanding and improved decision making. *james.hansen@nrlmry.navy.mil*

Dr. **David Kleinman** has been a Research Professor in the Command and Control (C2) Academic Group, Department of Information Sciences at NPS since 1994. From 1973-94 he was a Professor in the Electrical and Computer Engineering (ECE) Department at the University of Connecticut, where he founded and directed the CYBERLAB—a laboratory for *model-based* empirical research in cybernetic systems. Dr. Kleinman has over 35 years' experience in multihuman decision making, distributed interactive simulations, organizational design, and control and estimation theory. In 1993, he was elected a Fellow of the IEEE for his pioneering work in modeling human control and information processing performance. Dr. Kleinman's current efforts in human/C2 decision making include the empirical study of team and organizational performance, coordination, and adaptation processes in complex multitask environments. For almost 10 years, under ONR sponsorship, this work has been conducted in collaboration with faculty and students at the University of Connecticut. The success of the project is due in large part to Dr. Kleinman's ability to serve as the link between the warfighting labs and operational expertise resident at NPS and the strong modeling and simulation capabilities within the ECE Department at UConn. *dlkleinm@nps.edu*

Captain **Jeff Kline**, United States Navy (Ret.), is a Senior Lecturer in the Operations Research Department, holds the Chair of Warfare Innovation, and is the Program

Director for the Consortium for Robotics and Unmanned Systems Education and Research. He has over 26 years of extensive naval operational experience including commanding two U.S. Navy ships and serving as Deputy Operations for Commander, Sixth Fleet, where he participated in theater-wide operational planning. In addition to his sea service, Captain Kline spent three years as a Naval Analyst in the Office of the Secretary of Defense. Captain Kline is a 1992 graduate of the Naval Postgraduate School's Operations Research Program, where he earned the Chief of Naval Operations Award for Excellence in Operations Research and, in 1997, was a distinguished graduate of the National War College. Captain Kline's NPS faculty awards include the 2011 Institute for Operations Research and Management Science Teaching of Practice Award, the 2009 American Institute of Aeronautics and Astronautics Homeland Security Award, the 2007 Hamming Award for interdisciplinary research, the 2007 Wayne E. Meyers Award for Excellence in Systems Engineering Research, and the 2005 Northrup Grumman Award for Excellence in Systems Engineering. *jekline@nps.edu*

Krishna R. Pattipati is a UTC Professor in Systems Engineering in the department of Electrical and Computer Engineering at the University of Connecticut. His research interests are in the application of systems theory and optimization techniques to agile planning, fault diagnosis and prognosis in complex systems, multi-object tracking, and threat detection. Professor. Pattipati was elected a Fellow of the IEEE in 1995, for his *contributions to discrete-optimization algorithms for large-scale systems and team decision-making*. He served as Editor-in-Chief of the IEEE Transactions on SMC-Cybernetics (Part B) during 1998-2001. *Krishna@engr.uconn.edu*

Eva Regnier is Associate Professor in the Defense Resources Management Institute at the Naval Postgraduate School. She holds a Ph.D. in Industrial Engineering, an M.S. in Operations Research from the Georgia Institute of Technology, and a B.S. from the Massachusetts Institute of Technology. Her research is in decisions under uncertainty, including characterizing uncertainty for optimization and judgmental decision making, with a focus on applications with sources of uncertainty in the natural environment. Recent applications include predicting the geographic distribution of piracy risk and estimating the logistics burden associated with energy consumption. *eregnier@nps.edu*

Dr. **Johannes O. Royset** is an Associate Professor of Operations Research at the Naval Postgraduate School. Dr. Royset's research focuses on formulating and solving stochastic and deterministic optimization problems arising in complex systems, sensor allocation and control, and mission planning. He has a Ph.D. from the University of California at Berkeley (2002). Dr. Royset was awarded a National Research Council postdoctoral fellowship in 2003, a Young Investigator Award from the Air Force Office of Scientific Research in 2007, and the Barchi Prize as well as the MOR Journal Award from the Military Operations Research Society in 2009. He received the Carl E. and Jessie W. Menneken Faculty Award for Excellence in Scientific Research in 2010. Dr. Royset is an associate editor of *Operations Research*, *Naval Research Logistics*, *Journal of Optimization Theory and Applications*, and *Computational Optimization and Applications*. *joroyset@nps.edu*

Lawrence G. Shattuck (Colonel, United States Army, Retired) graduated from the United States Military Academy in 1976. His military service spanned thirty years with assignments in the United States and overseas, including Operations Desert Shield and

Desert Storm. Upon his retirement from the Army, he was appointed as a Senior Lecturer in the Operations Research Department at the Naval Postgraduate School, where he directs the Human Systems Integration Program. He holds a Master of Science degree from Rensselaer Polytechnic Institute in Human Factors Psychology and a Ph.D. from the Ohio State University in Cognitive Systems Engineering. He has been an active researcher in the domain of military command and control for two decades. *lgshattu@nps.edu*

Dashi Singham is a Research Assistant Professor in the Operations Department at the Naval Postgraduate School. She holds a Ph.D. in Operations Research from UC Berkeley, and her research areas are simulation and applied statistics. Her research focuses on simulation input uncertainty and output analysis methodology, with applications to healthcare, military, and geophysics models. *dsingham@nps.edu*

APPENDIX B. AGENDA

Targeting an Asymmetric Maritime Threat
March 13-14, 2012
Naval Postgraduate School
Monterey, CA

Tuesday, March 13

9:30-10 AM – Welcome and Introductions

10 AM-NOON – Mission Areas
Each participant is invited to describe the mission area(s) that s/he is working in, touching on:

- the nature of the threat, decision type, information sources, and any constraints or special considerations; and
- approaches to simulating the targets' motion and generating optimal courses of action.

Emanuel Coehlo –
1) Adaptive Sampling 2) Environmental Risk Mitigation 3) ASW Multistatic Networks
Steven Dennis – Acoustic Performance Surface
Raffaele Grasso – General purpose maritime operation support system
Tracy Haack – Radar/Comms/Sensor Performance in Complex Environments
Jim Hansen – 1) Small Boats 2) Anti-piracy
Mike Atkinson – Detecting Drug Traffickers (DTOs)
Eva Regnier – 1) Counter-smuggling 2) Comparison with counter-piracy
Krishna Pattipati – Dynamic Resource Management

NOON-1 PM – Lunch on site

1-2 PM – Consolidation

In this working session, we will identify common features of the various mission areas and produce a coherent definition of the problem.

In the process, we hope to answer questions that sponsors might pose, including: What is the most general version of this problem? Which solutions may be applicable to other mission areas? What makes this kind of problem challenging, i.e. why should we be working in this area? What are the hard, unsolved problems?

2-4:30 PM – Technology Transfer
Experts will give us brief overviews of relevant tools and research results that may be new to some participants. We anticipate that each participant will already be familiar with half of these.

2 Environmental Impacts on Sensors - Tracy Haack and Steve Dennis
2:30 Search and Detection – Johannes Royset
3 Optimization Algorithms – Krishna Pattipati
3:30 Human Factors – Larry Shattuck
4 Simulation – Dashi Singham

4:30-5 PM – Implementation Challenges
In this session, we will describe implementation challenges, including barriers to operationalizing research results and both anticipated and surprising constraints for operational use of decision support and recommendations. The goal is to understand at what stage of development these challenges and constraints should be considered.

6:45 PM – Dinner, Montrio Bistro, 414 Calle Principal Monterey, CA

Wednesday, March 14

9 – NOON – State of the Science
The goal of this working session is to identify and evaluate approaches that have been applied or may be applicable to any mission area related to targeting an asymmetric maritime threat. We also want to spell out features of a mission area make each approach more or less likely to be useful, and understand what is the appropriate level of model complexity, as a function of mission area. We will address specific portions of the problem, including modeling target motion and optimizing the geographical allocation of search and interdiction assets.

NOON – 2 PM Lunch and Wrap-up

APPENDIX C. MISSION AREAS BRIEFING

Mission Areas

Targeting an Asymmetric Maritime Threat
March 13-14, 2012
Naval Postgraduate School
Monterey, CA

Ocean Sensing w/UMVs

Targets: U/W Gliders, SHARCs

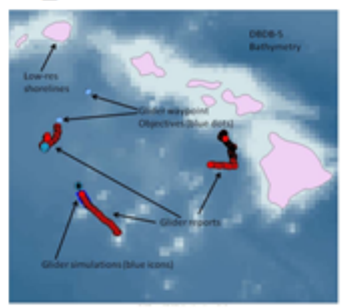
Location: All earth oceans.

Environment: Open ocean.

Information sources: METOC forecasts DBDB, DNC, GMBD, glider reports.

Decision type: UMV navigation to accomplish specified sampling goals.

Constraints/challenges:
Technical: Vessel speed < current speed
Operational: Present UMV mgmt. methods are labor intensive, automation is needed.



Mission planning system for u/w gliders showing bathymetry, shorelines, glider position reports and simulated movement with forecast currents.

Systems are being operated remotely from NAVO.

Acoustic Performance Surface

Target: Submarines

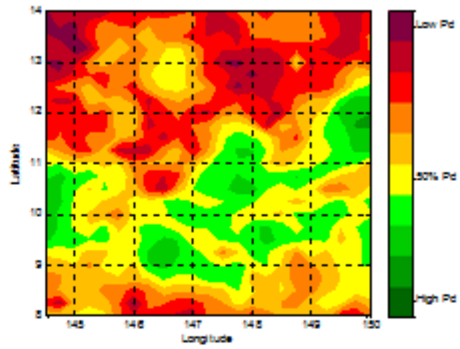
Location: Deep water ocean and littoral areas.

Environment: Coastal bases and maritime.

Information sources: METOC forecasts from FNMOC and NAVO, Acoustic propagation modeling from NRL and NAVO.

Decision type: Asset Allocation and Course Of Action.

Constraints/challenges: Ocean dynamics. Target uncertainty.



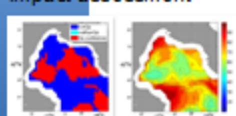
Predict target detection probability based upon operating environment, sensor type and target behavior.

NURC

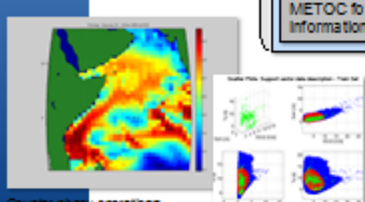
PARTNERING FOR MARITIME INNOVATION

General purpose maritime operation support system

Environmental impact assessment



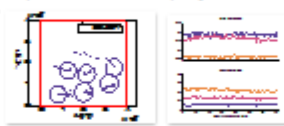
REA: underwater glider operations



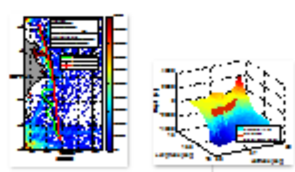
Counter piracy operations

- Multi-objective Decision Support, Sensitivity Analysis
- Multi-objective Mission Optimizer
- Mission metrics and risk scores
  - Subjective metrics
  - Objective metrics
- Dynamic and/or Kinematic model of assets
- METOC forecasts and non-METOC information, uncertainty …

Operation planning: optimal asset deployment



ASW: sono-buoys optimal placement



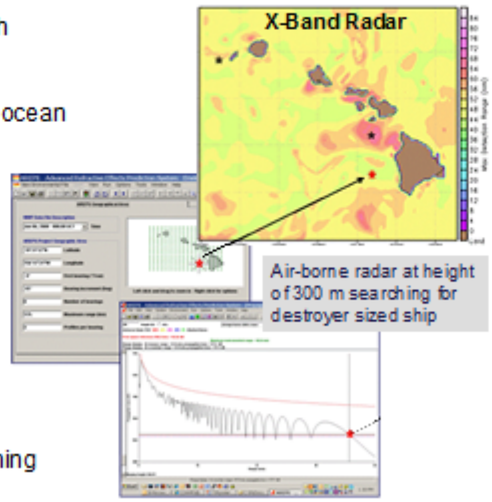
REA: underwater glider mission planning

NATO UNCLASSIFIED

Radar/Comms/Sensor Performance in Complex Environments

Target: Small near-surface targets such as boats, periscopes, missiles
Location: Global, On-Demand
Environment: Maritime, coastal, open ocean
Information sources: METOC from FNMOC, Sensor/target types from OS, propagation from COAMPS/APM predictions
Decision type: Sensor Performance
* Firm track range
* Maximum detection range
* Probability of detection

Constraints/challenges:
<u>Technical</u>: Accuracy, uncertainty
<u>Operational</u>: MP computational requirements, SIPR links, Training



Small boats

Target: Small attack craft, operating in groups

Location: within 100 miles of shore

Environment: Coastal bases and maritime.

Information sources: METOC forecasts from FNMOC and NAVO, INTEL from ONI, behavior from various.

Decision type: avoid, prepare, and defend

Constraints/challenges: Solution must account for gaming intrinsic in tactics.

Predict the vulnerability of blue forces to small boat attack as a function of tactics, location, and environment.

Anti-piracy

Target: Typically small skiffs and dhows.

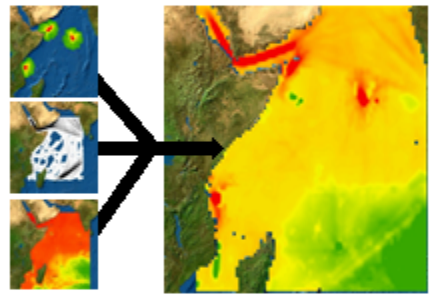
Location: 7.3 million square nautical miles in the west Indian Ocean and Arabian Sea.

Environment: Coastal bases and maritime.

Information sources: METOC forecasts from FNMOC and NAVO, INTEL from ONI, behavior from various.

Decision type: Where to send surveillance and interdiction assets.

Constraints/challenges:
Technical: Timely INTEL, latency, multi-national coordination.
Operational: Multi-national classified communications.



Pirate Attack Risk Surface (PARS) combines METOC, INTEL, and behavior information to predict distribution of pirate attacks.

Produced operationally at NAVO, disseminated to ONI and NAVCENT.

Detecting Drug Traffickers (DTOs)

Atkinson, Kress, Pietz, Royset

Target: Fishing vessels, go-fast, SPSS, SPFS

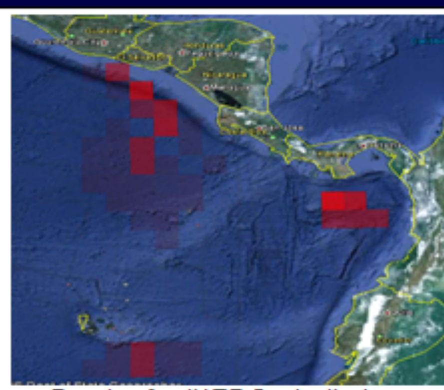
Location: Eastern Pacific and Caribbean

Environment: Coastal bases and maritime

Information sources: METOC conditions, SIGINT (e.g., radar, sonar), HUMINT, COMINT, historical patterns

Decision type: Where to send detection, surveillance, and interdiction assets.

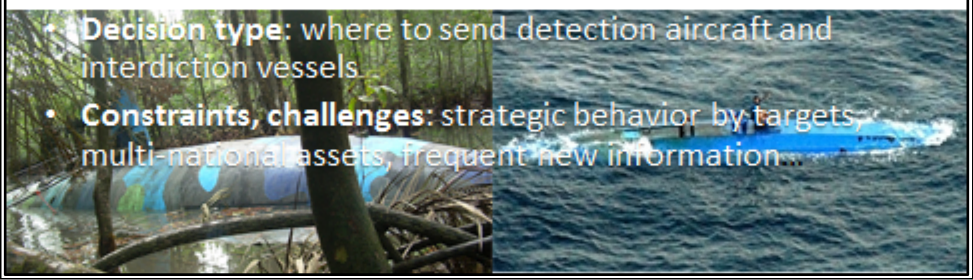
Constraints/challenges:
Intel: fusing different types (e.g., SIGINT vs. HUMINT) that pertain to past, present, and future
Time scale: short ("where to send whom now?") vs. long ("where to position assets?")



Develop for JIATF-S a tactical decision aid (DIMAT) that facilitates better situational awareness about the theater of operations, and provides guidance on where and when to deploy search assets during counter-drug operations.

Counter-smuggling

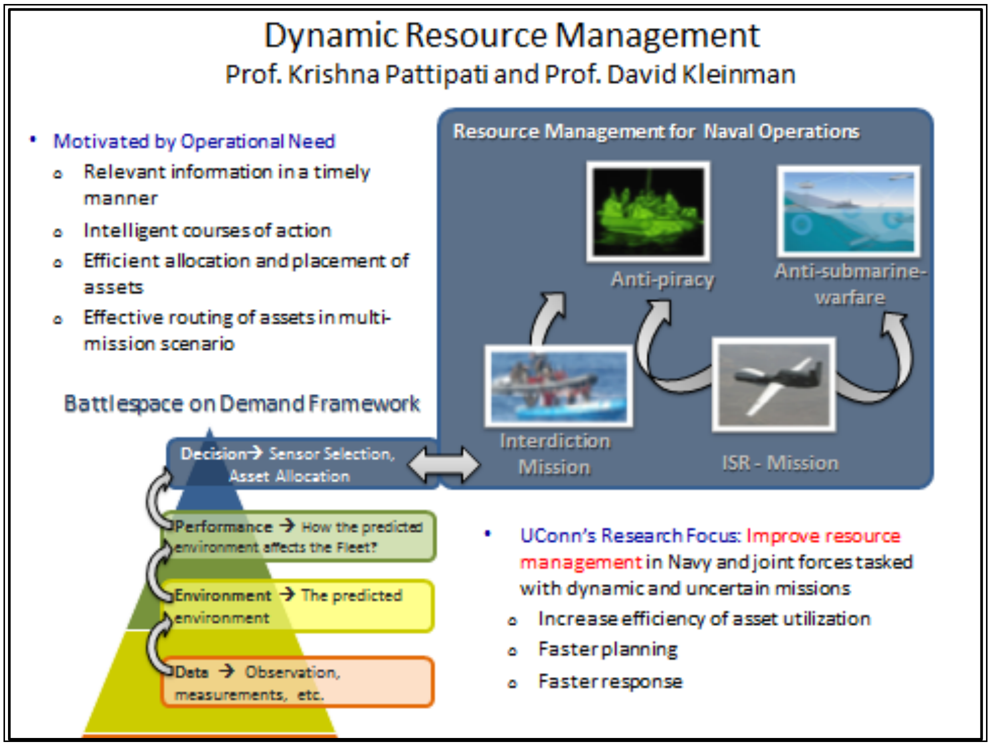
- **Targets**: varied, including semi-submersibles, may be hard to distinguish from neutrals
- **Location**: Caribbean and East Pacific (~10^6 sq mi)
- **Environment**: METOC affects detection, but may have little effect on targets
- **Information sources**: varied, including METOC, sensors, HUMINT, analyst assessments, etc.
- **Decision type**: where to send detection aircraft and interdiction vessels
- **Constraints, challenges**: strategic behavior by targets, multi-national assets, frequent new information



Counter-piracy vs. Counter-smuggling

- Targets do not reveal themselves
- Interdicting a given target may be very important
- Targets transit from origin to destination
- Smugglers not affected by METOC
- Detection heavily constrained by METOC
- Patrol boxes set daily

- Pirates reveal themselves by attacking
- Deterring pirate attacks is sufficient
- Foraging/hunting behavior
- Pirates very METOC sensitive
- Counter-piracy assets insensitive to METOC
- Stable(r) patrol areas



Dynamic Resource Management
Prof. Krishna Pattipati and Prof. David Kleinman
Motivated by Operational Need
Relevant information in a timely manner
Intelligent courses of action
Efficient allocation and placement of assets
Effective routing of assets in multi-mission scenario
Battlespace on Demand Framework
Decision → Sensor Selection, Asset Allocation
Performance → How the predicted environment affects the Fleet?
Environment → The predicted environment
Data → Observation, measurements, etc.
Resource Management for Naval Operations
Anti-piracy
Anti-submarine-warfare
Interdiction Mission
ISR - Mission
UConn's Research Focus: Improve resource management in Navy and joint forces tasked with dynamic and uncertain missions
Increase efficiency of asset utilization
Faster planning
Faster response

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