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SIMULATING PIRATE BEHAVIOR TO EXPLOIT ENVIRONMENTAL INFORMATION

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ABSTRACT

Recent years have seen an upsurge in piracy, particularly off the Horn of Africa. Piracy differs from other asymmetric threats, such as terrorism, in that it is economically motivated. Pirates operating off East Africa have threatened maritime safety and cost commercial shipping billions of dollars paid in ransom. Piracy in this region is conducted from small boats which can only survive for a few days away from their base of operations, have limited survival in severe weather, and cannot perform boarding operations in high wind or sea state conditions. In this study we use agent models and statistical design of experiments to gain insight into how meteorological and oceanographic forecasts can used to dynamically predict relative risks for commercial shipping.

1 BACKGROUND

Due to the increase in pirate activity off the coast of Somalia (Murphy 2009), the United States military and the combined forces of the worlds navies are partnering together to defeat these violent extremists. Piracy has threatened maritime safety and cost commercial shipping billions of dollars paid in ransom monies. The Gulf of Aden and the Horn of Africa were once safe to transit, but are no longer so. For this reason, President Obama has issued an executive order to defeat terrorism in the form of piracy. The Commander of the U.S. Naval Forces Central Command (CENTCOM), U.S. Fifth Fleet, Combined Maritime Forces (CMF), is responsible for the safety, stability, peace, and vital interests of the United States for 2.5 million square miles of water. In this paper, we focus on the Somali geographical region where pirate attacks have been most concentrated. Combined Task Force 151 (CTF 151) is a multi-national task force that is responsible for 1.1 million square miles of water in the Gulf of Aden and off the coast of Somalia.

Pirates in this area generally operate from small boats (skiffs) that have limited survivability at sea in severe weather conditions. We will refer to these as METOC (Meteorology and Oceanography) conditions. High sea state and/or wind speeds make it difficult or nearly impossible for pirates to attempt to board commercial vessels. Our analysis is intended to provide insight into what factors are most influential in contributing to and limiting pirate behavior.

In response to the piracy problem, the U.S. Naval Oceanographic Office (NAVOCEANO) at Stennis Space Center has been providing a forecasting product called the Piracy Performance Surface (PPS). The PPS uses forecasts of winds and seas to map the locations that are most conducive to pirate activity, and incorporates information on confirmed pirate activity in the form of an attack, an attempted attack, or suspicious activity. The existing product was developed rapidly to provide support to the operators. NAVOCEANO is working to improve the model of the relationship between METOC and pirate activity, and to improve the way the pirate threat is updated when confirmed piracy activity is observed.

The overarching research question is: How can the N2/N6 (Director for Information Dominance that comprises information, intelligence, command, and control) contribute decision-critical information to the operators who are protecting commercial shipping traffic?

By September 2010, a new simulation-based engine will be implemented to produce the PPSNext. The simulation is based on a model of pirate behavior (hereafter, CONOPS, Concept of Operations), combined with forecasts for METOC conditions and intelligence on certain parameters of pirate behavior, such as whether they operate from land or sea bases (mother ships) and the number and locations of those bases.

Our goal in this preliminary study is to provide insight on which factors describing pirate CONOPS are the most important drivers of the map reflecting relative pirate threat and which have the strongest interaction with METOC variables. These results would indicate which parameters in pirate CONOPS are most important to include in the model and should receive most intelligence resources.

2 SIMULATING PIRATES AND ENVIRONMENT

In the model of pirate CONOPS, the basic pirate strategy is to depart from a base—either a land-based camp or a sea-based mother ship—typically in a Boston Whaler that has longer longevity and life expectancy at sea, with a handful of pirates and a few days supplies. The skiff motors to its pre-determined location (latitude and longitude). As illustrated in Figure 1, the skiff then drifts with the winds and currents until the pirates run out of supplies, at which point the skiff motors back to its land or sea base.

Winds, waves, and currents affect the pirates. In their drift phase, their motion is determined by currents and winds. In addition, one of the factors whose impact we are evaluating is whether pirates use weather forecast knowledge to plan and implement an attack. In the current implementation, if the pirates have forecast knowledge it is assumed that their information is perfect. If they have forecast knowledge they do not go to locations with unacceptable weather, as determined by wind and wave thresholds. If they do not have forecast knowledge and encounter unacceptable weather, they return to their base location.

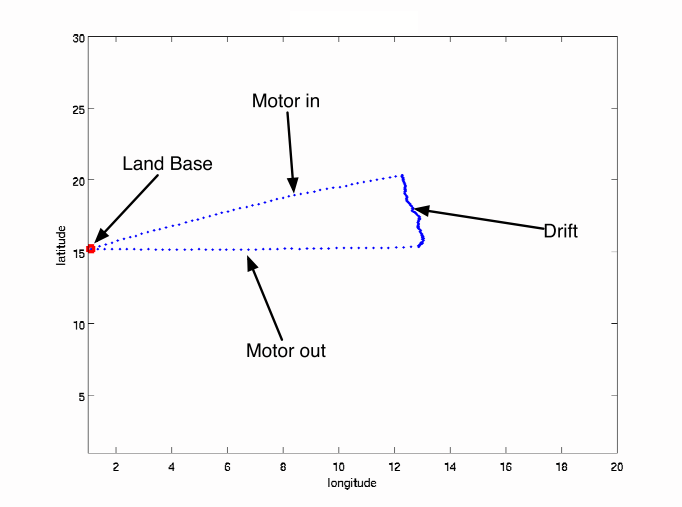

Figure 1: Example of a pirate skiff trajectory.

In the PPSNext operational implementation, the METOC conditions will be the result of a coupled atmospheric-oceanic model. In the prototype model used for this preliminary analysis, notional winds, seas, and currents(shown in Figure 2) change over the course of the 72-hour simulation, but otherwise do not vary as a function of simulation trial. The pirates operate in a 20×30-cell grid, with each cell 10 km on a side.

3 OUTPUT STATISTICS

3.1 Considerations

Perhaps the biggest challenge is how to summarize the simulations output. Although there is a limited database of historical pirate attacks, it has not been possible so far to recreate the METOC conditions corresponding to the period of known pirate activity against which to verify the model. Therefore, for these preliminary experiments there is no ground truth against which to compare results. In addition, even if we consider only the relative density of pirate activity across the simulated area and summarize pirate activity in 12-hour periods, each simulation produces a pirate density in each of 600 cells at each of six time periods (See Figure 3). Each simulation must be summarized and compared usefully with the results for other design points to identify the variables that are most influential and most related with METOC conditions.

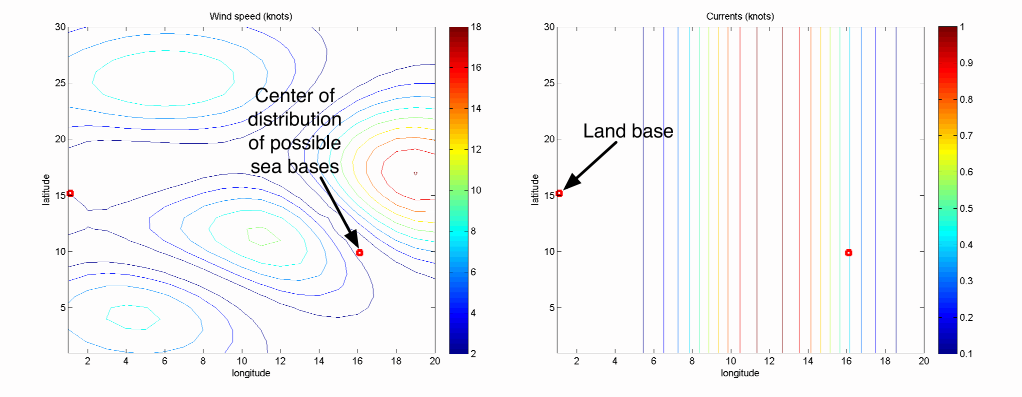

Figure 2: Simulated wind and currents.

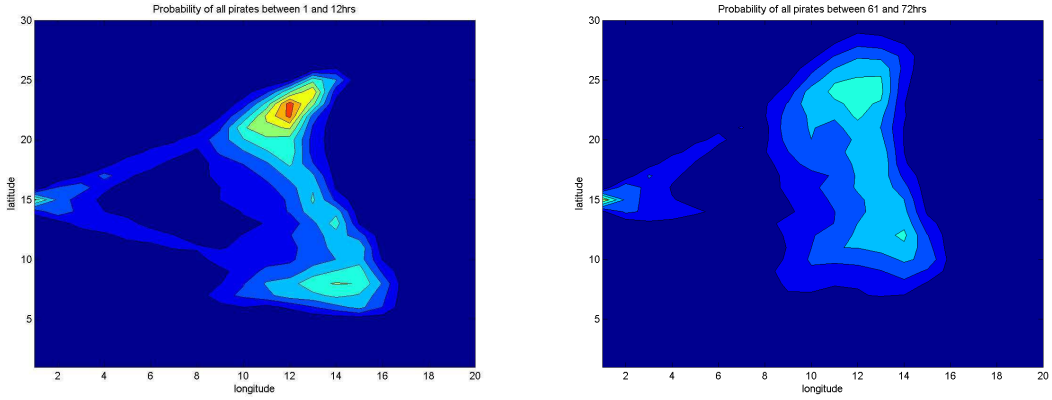

Figure 3: Sample PPSNext simulation output.

As described in Section 4, we undertook an experiment with a single replication of 33 design points, yielding 33 simulation runs. Within each simulation, differences across the six time periods would reflect sensitivity to METOC conditions (which changes over the course of the 72 simulated hours) and interactions with METOC conditions. Comparing the six pirate density plots would result in 15 pairwise comparisons. This suggests that some means of automating the process should be considered for larger future studies.

3.2 Potential Summary Statistics

We considered a variety of potential summary statistics for comparing two maps of pirate density (whether they were from the same time period, and different design points, or the same design point, but different time periods). The following measures were used as response-variables in our experiment:

- The maximum root mean square cell-by-cell difference (RMSE) between each design point and all other design points. RMSE especially penalizes large errors.
- The cell-wise maximum difference (MaxDiff) in pirate density between each design point and all other design points.
- For each trial, the largest RMSE between a 12hr pirate density and the 72-hour averaged pirate density map (this response variable is called ΔRMSE, and analogous measures are ΔMaxDiff and $\Delta 50^{th}$ percentile).
- The mean across time-periods of the area that bounds 50% of the pirate density (50^{th} percentile).
- Smoothed variations of each of the above, indicated by an S-prefix.

Other summary statistics that we considered, and which might be applicable in future work include:

- Cell-by-cell differences in mean relative entropy.
- Location: minimum distance between two modes (or sum of minimum 2 or 3 distances).
- Decision-related:
  - How much of the total pirate density can be captured within n miles of m optimally deployed search assets?
  - How big would a circular covering disk have to be to capture 75% of the pirate density?
  - Sum of differences over larger (coarse-grained) cells that might be defined according to the size of an area searchable by Task Force 151 assets within a given time.
- Other:
  - Bivariate Fourier transform of the pirate density grid.
  - Max eigenvector of the pirate density grid.

4 EXPERIMENTAL DESIGN

Because the current implementation of the simulation is in Matlab (Mathworks 2010) we expected each trial to take an hour or two to run, so we knew we would be limited in the number of design points we could explore within the time available for the initial study. To capture the effects of all variables and interactions among them, we used a Nearly Orthogonal Latin Hypercube (NOLH) design (Cioppa and Lucas 2007), downloaded from the SEED Center (2010). We restricted ourselves to an eleven factor experimental design with 33 design points. The factors and their maximum and minimum values are shown in Table 1 below.

Table 1: Factors and factor ranges studied in the experimental design. Summary names for later reference are in square brackets. Starred factors are used to calculate the number of land bases [Camps] and sea bases [Sea Bases].

Factor	Minimum	Maximum
simulated pirates per day	200	1200
mission length (hours) [Length]	72	120
number of pirate groups	3	7
total number of land and sea bases*	3	7
proportion of bases that are sea bases*	0.25	0.5
known base locations (Yes/No)	No	Yes
transit speed (kts) [Speed]	8	12
pirates' wind threshold (kts) [Wind]	10	20
pirates' wave threshold (ft) [Wave]	3	10
probability that pirates use forecasts	0.0	1.0
wind drift [Drift]	0.1	0.75

5 RESULTS

For each response variable, we used JMP statistical software to fit a regression model to a set of 75 potential predictors, i.e., the variables shown in Table 1, their squares, and all second-order (pairwise) interaction terms. JMP performed stepwise regression, allowing variables to enter and leave the model based on their significance (p-value).

Table 2 shows the factors that were included in each model, as well as the adjusted R^2 for each model. Wave threshold and wind threshold proved to be the most significant factors in the current Matlab implementation of the PPSNext model, with at least one of these two variables appearing in the model for every response variable except MaxDiff, which is the weakest of the response models. Also note that Wind and/or Wave are among the top two influential factors in all cases other than the MaxDiff model.

The absence of some factors from this set of models is very interesting. For example, these results seem to indicate that it is not important for intelligence to learn whether pirates can acquire and use METOC forecasts, nor would it change the PPSNext if they acquired that capability.

The Δ-prefixed response variables measure differences within a single simulation (design point) over the 72-hour simulated time period, rather than differences relative to the other design points. Therefore, the X-variables that are most related to the Δ Y-variables can be interpreted as those that have the largest interaction with METOC conditions. Both wind and wave thresholds appear in the model for every Δ response variable, indicating (not unexpectedly) that wind and wave thresholds interact strongly with METOC conditions in determining the spatial distribution of pirate activity. The wind drift factor and mission length do not appear in any of these models, however, indicating that they do not interact strongly with METOC conditions.

Factors that might be estimated using intelligence also appear to drive the results, in particular mission length. The interaction between mission length and wind threshold in two of the models is interesting. The number of sea bases

Table 2: Summary of the regression models for each response variable, detailing the adjusted R^2 and the statistically significant input factors ordered from most to least influential.

RMSE	S-RMSE	MaxDiff	ΔRMSE	S-ΔRMSE	ΔMaxDiff	S-ΔMaxDiff	50^{th}%-ile	S-50^{th}%-ile
0.77	0.68	0.38	0.55	0.77	0.66	0.84	0.73	0.71
Length × Wind	Length	Speed × Drift	Wind	Wave	Wave	Wave	Length	Length
Wave × Wave	Wind	Drift	Wave	Wind	Wind	Wave × Wave	Wind	Wind
Wave	Wave	Speed		Camps × Wave	Sea Bases	Camps	Sea Bases	Speed
Drift	Length × Wind			Camps	Sea Bases × Wave	Wind	Speed	Sea Bases
Camps × Drift	Wave × Wave					Camps × Wind	Sea Bases × Speed	Wave
Camps								
Length								

or camps—which are highly related, as the number of sea bases is a fraction of the total number of bases—appear in many of the models, indicating that it would be valuable to have good estimates of the number of bases.

The results do not provide clear guidance as to which of the output measures are more useful. In addition, smoothing does not have a consistent effect on the significance of the results. For some measures, the smoothed output model achieves greater R^2 than the raw value and for some measures the opposite occurs. The smoothed MaxDiff did not produce any factors that were significant at the $\alpha = 0.01$ level, and therefore its model is not shown in Table 2.

6 FUTURE WORK

Near-term future work on this project, to be completed in the next year, includes running similar experiments using the operational code. The improved model will include environmental and navigational conditions for specific, real areas of operations (in particular the area off the HOA plus the Gulf of Aden). We will seek to confirm the qualitative results of this preliminary study, and to identify which aspects of pirate CONOPS are most critical in interaction with METOC conditions and METOC uncertainty.

Another major component of future work is the possibility of building an agent-based model that will be able to represent other factors that we know to be important to the problem of detecting and protecting against the pirate threat. In particular, we would like to add agents that represent commercial shipping, searchers, and neutral vessels. We have begun researching modeling platforms for implementing an agent-based piracy model and the key features that we would like to see included. Two possible candidates are Pythagoras (Northrup Grumman 2008) and MANA (Lauren and Stephen 2002). One of the potential benefits of using either of these agent-based modeling platforms is the ability to run a multitude of simulations quickly.

MANA and Pythagoras offer slightly different feature sets, which can be important for modeling a specific scenario. For instance, Abel (2009) used MANA productively to model frigate defense effectiveness against pirate activity because MANA enabled him to model quadrant dimensionality of the frigate in the form of port, starboard, fore, and aft. This was essential for understanding weapons coverage in defending a frigate. However, our investigations indicate that MANA does not currently have the model flexibility that we need to study METOC conditions.

Pythagoras has the flexibility to model pirate behaviors such as seasickness, and to incorporate behaviors such as deciding to return to base after running out of supplies such as food or water. On the negative side, Pythagoras cannot model METOC as fluid dynamics since weather conditions change with each time step. METOC would be static while the agents would be dynamic. Although this feature is not represented in the current pirate simulation, it would be useful to model agents that lack perfect information about METOC conditions. This would be a more realistic representation for using a forecast.

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