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Bayesian Search Study for USW

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BAYESIAN SEARCH STUDY FOR USW

EXECUTIVE SUMMARY

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Project Summary
Adversarial submarine activity in the Atlantic has steadily intensified over the last few years. Furthermore, strategic adversaries have developed sophisticated and stealthy submarines, making them much more difficult to locate. This heightened activity, coupled with advanced platforms, has allowed the United States' adversaries to challenge its dominance in the underwater domain. Though extensive research has been performed on optimized search strategies using Bayesian search methods, most methodologies in the open literature focus on search for stationary objects rather than a search for a moving Red submarine conducted by a Blue submarine. Thusly motivated, we developed a model of an enemy submarine whose goal is to avoid detection. As the search effort is extended, a posterior probability distribution for the enemy submarine's location is calculated based off negative search results. We present a methodology for finding a search pattern that attempts to maximize the probability of detection in a Bayesian framework utilizing Markovian properties. Specifically, we study three different running window methods: a simple network optimization model; a network optimization model that performs updates after every time-period for the entire time horizon; and a dynamic program that only looks two time periods ahead.

Keywords: *Anti-Submarine Warfare, Optimal Search, Bayesian Search, Markovian Movement*.

Background
Submarine activity in the Atlantic Ocean has steadily intensified in recent years with the increased deployment of adversaries' submarines. Additionally, U.S. adversaries are developing highly capable and stealthy submarines equivalent to those in the U.S. Navy. Because of these developments, U.S. senior leaders have assessed that the Atlantic Ocean is no longer an uncontested battlefield; new considerable undersea threats have emerged. For example, in 2018, the USN reestablished the U.S. Second Fleet to counter adversarial submarine activity in the Atlantic (LaGrone, 2018). In addition, the Navy recently announced the creation of a new task force of destroyers specifically assigned to be ready on short notice to deploy for hunting submarines in the Atlantic (Shelbourne, 2021). Operationally, crews are receiving extra training and certifications prior to deployments, to ensure readiness to face the undersea threat from hostile submarines. The actions the USN is taking unambiguously illustrate the significance of the threat posed to national security by heightened hostile submarine presence in the Atlantic. Being able to quickly locate and track Red submarines, as they deploy to the Atlantic, is vital to national security. The Ohio-Class Ballistic Missile Submarines (SSBNs) were designed to be the survivable leg of the nuclear triad. Submarine crews on SSBNs, while on alert, are required to remain undetected so there remains a credible second nuclear strike capability, which offers the president additional flexibility in decision-making and presents a deterrence of nuclear and non-nuclear aggression by strategic adversaries. Hostile submarine activity operating in waters near SSBNs potentially degrades the survivability of the SSBNs, should the submarines detect and track them. The ability to quickly locate hostile submarines will allow commanders to adjust the location of SSBNs to maintain maximum assurance of their survivability and will help the Navy track the Red submarines to alleviate the threat of their weapons being deployed on the homeland.

From a historical perspective, Anti-Submarine Warfare (ASW) began in earnest during World War I to counter the Imperial German Navy's strategy of unrestricted submarine warfare (Cares, 2021). Since then, ASW has evolved into two categories: offensive ASW and defensive ASW (Cares, 2021). In offensive ASW, the goal is to hunt and kill enemy submarines (Cares, 2021). However, it is critical to note that during peacetime operations, the goal is modified to locate and maintain contact with the adversarial submarine (Cares, 2021). On the other hand, the goal in defensive ASW is to defend assets from being attacked by enemy submarines (Cares, 2021). What is common to both efforts is the need to efficiently find enemy submarines. Submarine commanders are given water-space within which to operate, information regarding a position of an adversary submarine, and possibly intelligence regarding the adversary submarine's mission. With this information, commanders are required to develop a plan to search for the adversary submarine, often over planning horizons (e.g., 12 hours). Our research is focused at facilitating this type of planning.

Findings and Conclusions

The ability to quickly locate adversarial submarines provides flexibility in the deployment of the USN strategic submarines, and it also provides security from attacks against the homeland. We developed algorithms that can aid decision makers aboard a submarine in their search for adversarial submarines. These algorithms may be further developed into operational decision tools that can be implemented during operations.

The first algorithm maximizes the probability of detecting Red over the time horizon, using a network optimization framework. The search plan is calculated once and without updates, assuming that Red is not detected in a searched cell. We then expand upon this algorithm by performing a Bayesian update of the position of a Red target after each cell search, assuming that the search is unsuccessful. Following a Bayesian update, a new search plan that maximizes the probability of detecting the Red target in the remaining search period is computed. The third algorithm is a dynamic programming model. The algorithm also makes use of Bayesian updates which assume the cell search is unsuccessful; however, in this algorithm, instead of maximizing the probability of detecting Red over the entire remaining planning horizon, we maximize the probability of finding Red in the next time period or, failing that, in the following time period.

To compare the three algorithms, we pose five scenarios where we vary the starting location of the Red target and the number of cells in which it may initially be located. The transition matrix governing Red's movement is the same in the first four scenarios; it permits Red to to move in a certain general direction. The fifth and sixth scenarios are more relaxed. For each scenario, 10,000 initial starting positions and routes are simulated.

Using the optimal search plans and the simulated routes for Red, we determine if Blue detects Red and during which period the search plan detects Red. We compute 95% confidence intervals for the probability of detecting Red and generate empirical CDFs to illustrate how the probability of detecting Red varies with time to compare the three algorithms. Additionally, for the first five scenarios, we calculate the computational time required to generate the search plan for each algorithm in CPU cycles.

The results of the first five scenarios are consistent: The second and third algorithms outperform the first algorithm, the third algorithm the second in four of the first five scenarios; however, in all five scenarios the 95% confidence intervals for the probability of detection overlap, meaning their performances are comparable. These computational results show that the third algorithm is the most computationally efficient, which makes it the best algorithm to implement in a search tool.

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Recommendations for Further Research

We recommend in future research to explore non-perfect sensors where there are both false positive and false negative search results, and where the probability of detecting Red, if both submarines are in the same cell, is less than one. This will allow for more realistic conditions where environmental factors play into how well an adversarial submarine may be detected. We also leave for future work relaxing the assumptions that the transition matrix is known by Blue and using concepts from Game Theory to explore worst-case transition matrices for Blue—the searcher.

Finally, applying the work in this report to multiple search assets conducting the search concurrently is an important problem that may well require a different modeling approach.

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Acronyms

ASW	Anti-Submarine Warfare
SSBN	Nuclear Ballistic Missiles Submarine