Modeling Missing Maritime Objects Using an Agent Based Model

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Abstract: Accurate modeling the movement and behaviors of missing persons and vessels is critical in their finding and rescuing in maritime environments. Current methods focus on using particle techniques that model several factors including leeway and drift but lack the ability to model human factors and behaviors. This research explores the idea of using an agent-based approach to model missing objects with the goal of developing a methodology that accounts for missing person behavior in a maritime domain. This new approach leads to a more accurate missing persons movement trajectories and results in finding better search plans. The results show that an agent-based model can consider environmental elements, behavioral factors, and hazards when modeling target movement in a maritime domain which is critical in missing object modeling. The developed approach also shows how an agent-based model can help find optimal search plans.

1 INTRODUCTION

In this paper we examine and discuss the use of an agent-based model (ABM) in modeling missing maritime objects. Using a ABM could increase the accuracy of predicting how missing maritime objects move by modeling human factors and behavior.

The motivation of this research is to increase the probability of search and rescue (SAR) personnel finding missing persons and saving lives. Between 1993 and 2016, an average of 278 lives were lost annually after the United States Coast Guard (USCG) was notified of a missing person. (U.S. Coast Guard, 2019).

Consider a scenario that is loosely set on the eastern shore of Delaware. Consider yourself a manager of SAR operations who develops, implements, and oversees SAR activities in the area. It is a cool autumn day at a well-known coastline. There is a strong wind that shifts from the south to the east at 10 knots, and the sky is clear and cool. From New Jersey, the water currents travel south before turning east to join the Gulf Stream, which travels northwest. There have been emergency calls, so a search operation needs to be started.

The distress signal is sent by a fishing boat. The boat's operators claim that electrical problems. are impacting their motor and navigational gear. The caller said they were travelling northeast but weren't aware of their precise location. The call was cut off, and attempts to reach the other party were futile. The emergency radio call was triangulated to get the last known location. There are helicopters, cutters, and search boats among the search resources at hand.

Such a situation requires a quick turnaround in terms of decision making and launching a SAR operation. The methodology described in this manuscript helps a SAR manager make qualified decisions that maximize the probability of finding the lost boat considering available resources.

2 LITERATURE REVIEW

How a search theory methodology simulates target movement is a key element in any search plan optimization for a mobile target. Historically, diffusion methods have been widely applied (Lin & Goodrich, 2010) and (Eagle, 1984), whereas SAROPS (Search and Rescue Operations Planning

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System) currently employs a particle technique. (Kratzke, Stone, & Frost, 2010) Applying an ABM in wilderness searches has been studied in some detail (Mohibullah & Julie, 2013). A few case studies have also been done to use agent-based simulations to marine search operations in order to enhance verification and validation techniques (Onggo & Karatas, 2016).

The majority of pertinent research on the employment of ABM in maritime settings is concentrated on military and security uses. Port security (Harris, Dixon, Dunn D.L., & Romich, 2013) and the use of UAVs for surface monitoring (Steele, 2004) are examples of this. Additionally, a number of studies, including (Walton, Paulo, McCarthy, & Vaidyanathn, 2005) and (Sullivan, 2016), have been published on force protection simulations. The employment of ABM in counter-piracy activities has also been studied by numerous scholars (Deraeve, Anderson, & Low, 2010), (Dabrowski & Villiers, 2015), and (Marchione, Johnson, & Wilson, 2014). The verification and validation of these models, as seen, for instance, while examining tactics to defend cargo ships against pirate attack (Deraeve, Anderson, & Low, 2010), is a frequent problem in this field of research. However, the methods utilized to evaluate and verify the simulations are not explicitly stated.

The Pathfinder methodology introduced in (Grewe & Griva, 2022) and (Grewe & Griva, 2022) allows finding optimal SAR plans that maximize the probability of target detection with available recourses. While these manuscripts can offer a high-level overview of the Pathfinder methodology, the present manuscript focuses on ABM portion of Pathfinder.

2.1 Limitations of Diffusion Methods

Diffusion methods have been used several times to model mobile targets and have been applied in several search theory methodologies (Eagle, 1984); plus to model lost persons (Lin & Goodrich, 2010). These techniques, which rely on Bayesian statistics and probabilities, can get more difficult as the terrain gets more complicated. It may work in the open ocean but terrains like bays, marches, etc are far harder to model. The main problem is that targets' independence as independent agents with decision-making abilities is not considered by diffusion methods. Additionally, they are unable to model changes in target type or survival mode. Because of these limitations, the diffusion method can only adequately model simple targets or objects over a unified terrain.

2.2 Limitations of Particle Methods

The particle method considers only environmental factors, while in addition to that the ABM can also account for various behavioral modes of a target. Each agent may have a special trajectory based on agent's individual behavioral characteristics. Therefore, the ABM covers a much wider range of possible target movements, types, transitions, and thus results in search plans with higher probabilities of finding missing targets.

3 PATHFINDER METHODOLOGY

This section discusses Pathfinder, starting with an abstract overview and then breaking down Pathfinder into its core components. Next, we will review the relevant models, processes, and definitions.

Pathfinder is a comprehensive search theory methodology that uses an ABM to model target movement and a nonlinear optimization model to find optimal search paths. This is a powerful blend of technology that has several advantages over existing methodologies. (Grewe & Griva, 2022).

3.1 Components

The nonlinear optimization model and the ABM are the two main parts of Pathfinder. While each element can be used independently to enhance an existing search methodology, their combined use is especially potent. The ABM incorporates both environmental and historical data. The nonlinear optimization model will produce the best search plans for the maritime search operation after receiving the information from the ABM. The relationship between these elements and search operations and data is shown in **Figure 1**.

3.2 Design

Figure 1 shows the breakdown of proposed rescue operations into logical sub-processes. It serves as the basis for the Pathfinder design. Only two of Pathfinder's many automated and sequential sub-processes require human involvement. This manuscript describes in detail each sub-process necessary for the core components—ABM and optimization model—to function properly.

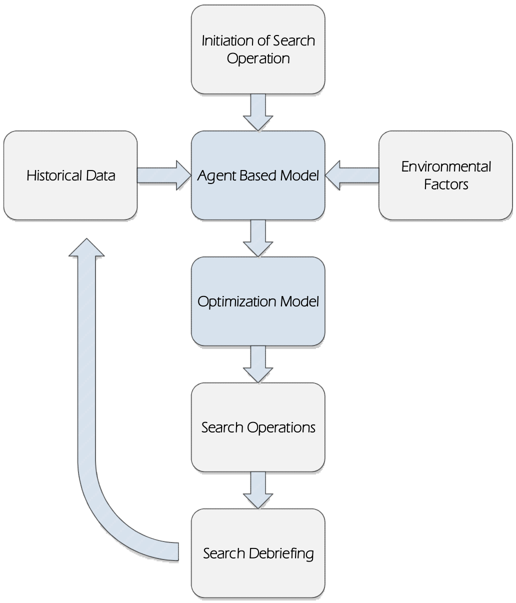

Figure 1: The relationship between search operations and the two main Pathfinder components, ABM and optimization model.

The steps in this new methodology are introduced in this section. Each phase has a separate sub-process that is essential to the operation of Pathfinder. The setup procedure comes first. The search manager chooses search-specific information in this step, including target types, searcher types, domain, and last known location. Pathfinder then starts processes that load history data, topography data, and environmental data after the search manager makes these selections. The Epsilon model is the next phase, and it is used to find restrictions on the searchers' travel across the domain. The ABM is the next step, which simulates target movement. The search manager is presented the findings after the ABM is concluded. The search manager enters a preliminary search plan using this information. Once entered, the pre-processor uses this initial search plan for the nonlinear optimization model. In addition, the pre-processor prepares the variables and data for the optimization model. The nonlinear optimization model then identifies the best search strategies for each searcher. After the nonlinear optimization model is finished, a post-processor is employed as a quality-control step and to get the data ready for visualization. The search plan is visualized at this point, along with any necessary data files. The search plans are now prepared for use in search operations by a search manager.

4 MODEL

4.1 Environmental Factors

Wind and water currents are the two main environmental elements that influence target movement. The following equations from the USCG (USCG, 2013) are used to compute the first element, leeway speed, or the movement induced by wind and waves, of a target. Assume $slope_g$ and $Yint_g$ are constants, plus L_s and W_s are the leeway speed and wind speed, respectively. These parameters vary based on the target type. The y-intercept and slope of the leeway linear equation are the constants $Yint_g$ and $slope_g$. Regression analysis and experimentation are used to find these constants (Morris, Osychny, & Turner, 2008). When $W_s < 6$ knots, the equation changes, resulting in $L_s = 0$ at $W_s = 0$.

$$L_s = \begin{cases} \{slope_g W_s + Yint_g \ \ for\ W_s \geq 6\ knots \\ \left(slope_g + \dfrac{Yint_g}{6}\right) W_s \ \ for\ W_s < 6\ knots \end{cases} \tag{1}$$

In the current prototype, this is a quick way to determine the leeway speed for various target types. For target types with a small $slope_g$, the future implementation of Pathfinder will additionally use the Rayleigh Method (Kratzke, Stone, & Frost, 2010). Water currents are the second environmental component. The vector sum of the existing currents in the environment is used to compute the overall water current. This calculation considers various currents, such as wind, surface, and tidal currents. Using historical data as well as information from organizations like NOAA, water currents will be gathered in a manner similar to SAROPS. Two environmental elements are present in the SAR scenario: a 10-knot wind and water currents that are moving from the south to the east into the northeast-moving Gulf Stream.

4.2 Hazards

Next we discuss hazards and their effects on target movement. Hazards that can cause death of a searched target are problematic to model. Hazards that interfere with target movement, however, are simpler and depend on other behavioral elements. Currently there is incomplete data on the probability of death due to hazards. There is, however, data on survival times for cold exposure (Tikuisis, 1995) The USCG has utilized this mathematical model to determine when to stop looking for a missing person in the water.

When a target agent expires, it will be due to the whims of wind, currents, and other environmental factors. More investigation is required to compile this data and model death because of exposure. One can, however, model an agent's ability to move around hazards such as jetties.

4.3 Behavioral Factors

Behavioral factors were based on "survival modes" which themselves are based on historical data and assigned to agents on setup. Koester lists eight different "survival strategies " that people who are lost could employ (Koester, 2008). Agents can switch between various "survival modes" while the search progresses. Five of the most popular survival strategies are included in the Pathfinder prototype: overdue, travel aide, route finding, staying put, and wanderer. Several survival modes are a subgroup of these five and can be modelled in the future; for example, direction sampling is a type of route finding. Based on the weather, geography, objective location, time of day, and other factors, the survival mode determines how each agent will act. The historical information utilized in the ABM was taken from (Koester, 2008), which has some useful information but not all the information required for a maritime environment. It will be crucial in the future to gather and derive data to adjust the ABM to a maritime environment. The next step is to go through each survival mode and how the ABM predicts target movement.

When the target agent is trying stay put and is not actively moving, it is in the *staying put* mode. The SAROPS concept of "stickiness," which is inherent in this ABM, is also present. If the water is shallow enough, an agent who has a way to stay put—like an anchor—might decide to use the anchor. The target may also beach and remain put if they are sufficiently close to the shoreline. The agent will have to struggle against the environment to remain immobile if they are unable to drop an anchor or beach their watercraft. The *wanderer* mode is for the target agent who, individually or in combination, (a) has no idea where they are, (b) has no idea where they wish to go, (c) may not be mentally competent of making reasonable decisions. When an agent is in this survival mode, they move randomly, frequently taking the simplest routes (Koester, 2008).

Overdue, *route finding*, and *travel aid* survival modes are all incorporated in the same way, but they have different end points in mind. Where the target agent wishes to go is the target destination. This might be a fishing spot, a boat ramp, or just a site in general. Each of these three survival strategies has a unique method for determining the location of this target. The target agent in the overdue mode is just overdue and not lost. As a result, the target agent's perception of their location and the target location is accurate. The travel aid mode is for a lost target agent who possesses navigational tools like a map or compass. As a result, a target agent's perception of its location and the target destination is generally accurate and becomes better as the agent approaches its destination. The target agent does not have a reliable estimation of their location or their destination in the route-finding mode. The target agent will move in a general direction until they come across landmarks that can direct them.

The ABM employs a genetic algorithm to simulate the target agent's route in order to model these three survival options. The "bounded rationality" principle is applied in this genetic algorithm (Simon, 1982). Time, information, and human capacity for reasoning are all constrained, which causes rationality to be bounded. A person seeking to navigate a space may have a map of what lies ahead, but until they are closer, they cannot see the specifics of the path. For instance, a boat dock might be indicated on a map as being ahead, but as the user approaches, they find it is damaged and unusable. Accordingly, the path that will most likely take place in the near future is the actual one, but the path in the *far* future is just an estimate.

The following paragraph describes how the genetic algorithm works. A straight path is made from the target agent's current location to its destination for t=0 and regularly during the modeled time, with each waypoint equally spaced and within the target agent's range of motion. If the target is late, the destination may be an accurate assessment, but if the target is lost and using a travel aids, the destination may be an inaccurate assessment of where its goal location is. For the route-finding mode, this straight line lays in one direction that is not necessarily in the direction of the destination. Following the creation of this first path, the target agent's current location serves as the starting point for the genetic algorithm to run on a small portion of the path. The portion of the future path that is rational can be referred to as the "genetic segment" or the "rational section" in this case. Each waypoint in this section is marginally altered until a faster, simpler, safer, more realistic, and within the target agent's capability alternate path is discovered.

The new route is assessed using a weighted score. The target's preferences for a new path determines these weights. A shorter path could be more valuable to some targets than an easy one. The genetic algorithm's scoring weights are based on data and research on previously lost individuals. Since there is only one terrain type to consider in this study—open water—these weights have no impact on target movement. As a result, the shorter route is always chosen.

The target agent advances along the path by one step after the path is created then moves on to the next target agent. The ABM advances to $t = t + 1$ once all agents have moved. With analysis and integration of historical target behavior, several ABM components will require additional fine-tuning.

Targets can be modeled leaving a search domain, which is another benefit of employing an ABM in this configuration. For example, if we use the ABM to model a lost boat in Ω, we also model boats leaving the search domain Ω_S. This is an important factor in SAR operations that enables search manager to calculate when to end a search.

Modeling transitions between target types and survival modes is a crucial ability for an ABM. For instance, if a search team is looking for a boat, they must consider the possibility that the boat has sunk or may not have any power. It is possible that the target is now a life raft or someone in the water if the boat has sunk. A methodology should take these transitions into account in order to accurately model target behavior and movement. An example of a transition a boat might go through during a search is shown in Figure 2. Keep in mind that there are a number of possible transitions in this straightforward example, some of which can happen repeatedly.

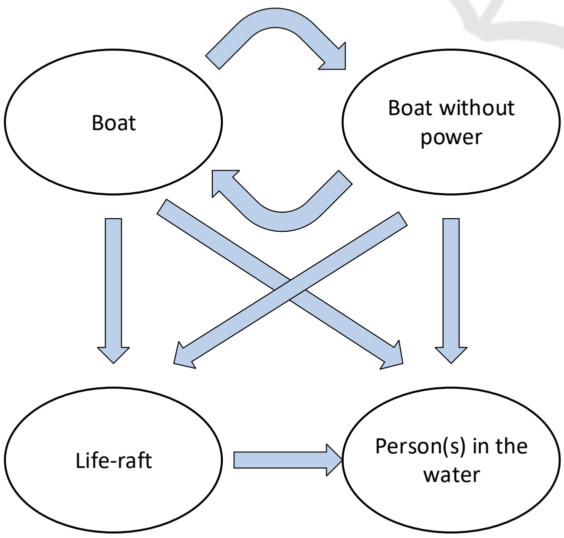

Figure 2: Visualization of the transitions that a boat could undergo. In order to accurately model target movement and behavior, these transitions must be modeled.

5 PRELIMINARY RESULTS

5.1 Analyzing Illustrative Scenario

Many of the actions and behaviors of agents in Pathfinder were modeled. Some of the agents are moved by the environment, some are propelled toward their objective if they have power, and some use an anchor in shallow water. High speed computing techniques seem to have the ability to train, tune, and optimize this ABM. In this scenario, there are two target kinds, and the model illustrates three different tactics a missing boat may use. The first visualization shows agent allocation, which is based on the three regions given to it, is shown in Figure 3. The agent colors are as follows; black are boats with power, green is boats without power, yellow are life rafts, and red are persons in water. Initial agent types are 60% boats with power, 30% boats without power, 5% are rafts in water, and the remaining 5% are persons in the water.

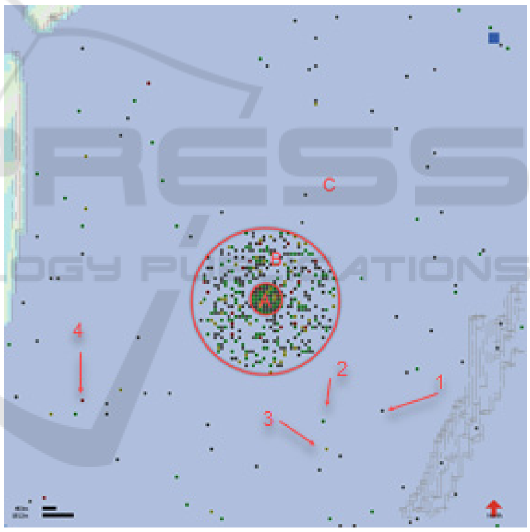

Figure 3: The three probability regions that were given to the initial agent allocation were: A) the 50% region, B) the 40% region, and C) the remaining 10% region. we used 1001 agents in this visualization. The agent colors are as follows, with examples; boats with power are black (1), boats without power are green (2), life rafts are yellow (3), and persons in water are red (4). Initial agent types are 60% boats with power, 30% boats without power, 5% are rafts in water, and the remaining 5% are persons in the water.

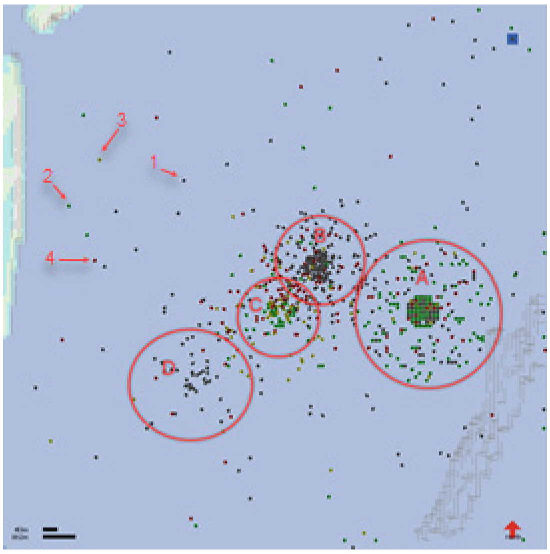

Figure 4: The agent's primary separated into four groups: A) an group of agents, primarily boats without power, that is traveling to its destination; B) a group of agents, primarily boats with power, that is being carried by the wind and currents; C) a group of agents, boats without power, that has anchored; and D) a group of agents, boats with power, that is traveling to the coastline In creating this visualization, we used 1001 agents. The agent colors are as follows, with examples; boats with power are black (1), boats without power are green (2), life rafts are yellow (3), and persons in water are red (4). Initial agent types are 60% boats with power, 30% boats without power, 5% are rafts in water, and the remaining 5% are persons in the water.

Figure 4 demonstrates yet another benefit of utilizing an ABM to simulate target behavior. When looking for a missing boat, keep in mind that it might or might not be powered, have an anchor deployed, capsize, sink, have life rafts in the water, or even have passengers in the water. As a result, there are various target categories that SAR operations may be searching for, and each target may display a variety of distinct characteristics. Because it can represent all conceivable target kinds and target behaviors simultaneously, the ABM is advantageous for search operations.

5.2 Analysis of the Number of Agents Needed

When employing this prototype, a crucial question arises: How many agents are required for an accurate analysis of target movement? While further consideration will be given to this in future research, our preliminary analysis demonstrates how the probability of detection (POD) and performance depend on the number of agents employed. We anticipate that utilizing more agents will improve modeling target behavior accuracy at the expense of performance; going from 100 to 500 agents would be preferred and advantageous for accuracy, despite an increase in processing time. Although increased precision from 5,000 to 50,000 agents might be slightly better, but performance could be greatly hampered. There must to be an ideal quantity of agents to be employed. With the next experiment, we will investigate how accuracy and performance are affected by the number of agents.

We will employ the initial search strategy shown in Figure 5 of a helicopter using a ladder pattern to search the domain. This preliminary search plan was made using USCG documentation.

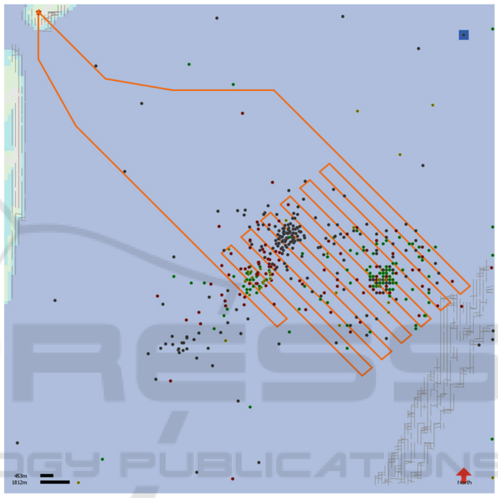

Figure 5: The initial search strategy for a helicopter (in orange) that will be used to assess the impact of Pathfinder's agent count.

With 1 to 2001 agents, we will conduct a number of experiments in Pathfinder. Then, for each series of runs, we will compile information on the searcher's runtime and distance covered. By looking at four agents from various prior distribution regions from a different run of the ABM, we will also examine POD. These agents will display the four main ABM movements: late, navigational aid, anchor deployment, and current-driven drifting. The use of these agents is necessary because the quantity of agents in the ABM will have an impact on Pathfinder's automatic POD calculation. So, in this experiment, we are testing the ability to find a single target by using these individual agents.

An almost linear growth in Pathfinder's runtime as a function of the number of agents was the first outcome. This was anticipated because the data source from the ABM extended the optimization model's runtime.

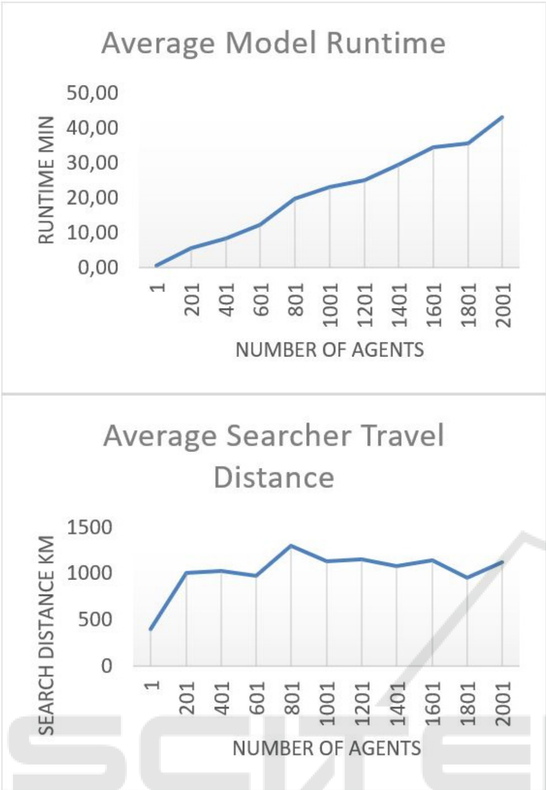

Figure 6: Top: The number of agents employed in the ABM vs the runtime in minutes for Pathfinder. Bottom, based on the number of agents deployed in the ABM and the average searcher travel distance in kilometers. Observe how it reaches a plateau because of the time constraints and searcher performance.

Next, we look at how the number of agents affect searcher travel distance. The searcher has a limited amount of time to search and can only move at a certain speed, so this effect was also anticipated. Around 1,320 km is the maximum distance that our searcher, a helicopter, can travel. In some experiments with 801 agents this limit was reached.

We expected that the POD would rise as the number of agents rose, but for agents coming from the 50% region, the POD peaks between 1000 and 1600 agents. There are peaks at 400 and 1000 agents for agents coming from the 40% region. Last but not least, using more agents did not significantly increase POD for agents in the 10% region. Since some modeling techniques, like SAROPS, use up to 10,000 particles to model a probability distribution, this was unexpected.

Future research should determine the ideal agent count and the reasons why, after 1000 agents, performance for agents inside the 50% region seems to decline but only slightly improves for those outside the 50% region. Many experiments we performed experience a drop in POD performance at around 501 agents. The impact of agents on the significant adjustments in search paths is related to this. The complexity of the plans rises along with the number of agents.

6 DISCUSSION

6.1 Verification Efforts

The output of the ABM is employed to verify simulation findings. During the verification process, numerous computations were used, and hundreds of executions were scrutinized. Agents were also examined to make sure they were produced properly and moved realistically inside the domain. This entails verifying calculations for movement, leeway, and drift.

An active verification process was used in the prototype after the static verification techniques. This was achieved by placing checkpoints throughout the prototype to resolve errors in calculations. For instance, targets situated on terrain types that are incompatible.

6.2 Validation Efforts

A critical research direction involves collecting more data for the ABM. More behavioral data is needed. For example, how often people in boats without power deploy their anchor or how often a missing kayaker will beach their kayak to conserve energy? This data needs to be collected and analyzed to finetune the ABM. The ABM is the component of Pathfinder that will need the most research and development in the future. This research will focus on both maritime and land scenarios.

7 CONCLUSION

The obtained results demonstrated that an ABM can aid in developing the search plans in a marine environment. When simulating target movement, an ABM may take environmental factors, behavioral aspects, and hazards into account. This is crucial in scenarios where a missing person may choose various modes of behavior. Environmental elements are similar to those used in earlier techniques, such as

SAROPS. The results also provide some guidance on the number of agents needed in the ABM to accurately detect target activity and movement. At the same time we believe that the number of agents as well as finding the probabilistic distribution of various modes of agents' behavior require more investigation.

8 FUTURE RESEARCH

A crucial study direction entails obtaining more ABM data. More behavioral information is required, such as how frequently anchors are dropped by vessels without power or how frequently a missing kayaker beaches their kayak to save energy. Finding the path score weights for the genetic algorithm will also be important for land searches. Depending on the geography, this will influence the preferred paths of lost people. For the ABM to be improved, this information must be gathered and examined. The part of Pathfinder that will require the most future research and development is the ABM. Both maritime and land-based scenarios will be the focus of this study.

Data can be gathered in a variety of ways for adaptation and validation. One could first collaborate with the USCG and ask for authorization to gather data from their search efforts. With volunteers equipped with GPS devices, field experiments might be conducted. This strategy has limitations since people who are missing behave differently than others who are following the instruction to "act as if you are in a life threating situation." Modeling how people move across a wilderness or maritime terrain may benefit from data collection and analysis from wilderness parks and habitats like those mentioned by (Crooks, et al., 2015). Land SAR analysis will also be helpful. For instance, a right-handed person is more likely to turn right when there is a choice in direction (Koester, 2008). Finally, historical data can be employed, but it is challenging to get and it may have gaps. Many missing persons do not know the exact path they took before being found although data on where they were found can generally be ascertained.

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