Utilizing Survival Behavior Models to Optimize Path Plotting for Multi-UAV Swarms in Search and Rescue

Avni Garg (2025agarg@tjhsst.edu), Kaavya Borra (2025kborra@tjhsst.edu)

Thomas Jefferson High School for Science and Technology

Abstract

Search and Rescue (SAR) missions are becoming increasingly common with thousands of operations each year. These time sensitive operations use large amounts of money and are vital to saving lives. The survival chances of a missing person are high if found within the first day, but after 48 hours, they drastically drop to almost zero percent. UAVs have recently become popular due to their speed and efficiency; however many procedures don't implement effective optimization algorithms or don't take advantage of known human behaviors wasting precious time spent on the operation. The goal of our project is to decrease the overall time of SAR operations by incorporating survival behavior models with optimized path plotting for a multi-UAV swarm. We will create a probability map of the search region using the survival behavior models. This region is divided among the UAVs in the swarm with the corresponding probability map regions provided to the UAV. We will establish a new path plotting algorithm which utilizes our probability map of where the target is most likely to be. Each UAV searches the area, generally searching areas with higher probabilities over areas with lower probabilities utilizing ResNets for image recognition. If a target is detected, the ground search team would then be informed so they are able to retrieve the lost person. Our final algorithm will be tested on DJI's flight simulator. We hope to see amazing improvement from the current SAR protocols, and that our research can be implemented in real-life SAR missions.

Rationale

Search and Rescue (SAR) operations are important investigative missions that are used in scenarios when an individual goes missing in a dangerous place. As per standard practices, when the subject is not found within the initial investigation period, the search operation expands to a much larger scale which could last days or even weeks (Phillips et al., 2014, p. 167). It is crucial to maximize the efficiency of these operations, as they are becoming more common. The National Park Service (NPS) reported that SAR missions in national parks have been increasing, from around 1403 in January to June 2018 to almost 1470 in the same months in 2021 (Sonken, 2021). Additionally, time is vital in search and rescue with almost no surviving targets 50 hours after targets declared missing (Adams et al., 2007, p. 100). SAR missions with drones show a quicker time-to-locate; however, the mission without drones was more successful in terms of finding the target. This could be attributed to lack of algorithm or strategy implemented in the mission with drones (Eyerman et al, 2018). Therefore, in order to decrease the search time and increase survival rates we can combine several optimization techniques.

Multi-UAV swarms are more effective than single-UAV systems, based on factors such as survivability, scalability, speed, autonomy, cost, communication, and radar. One way to implement a multi-UAV system is by having a group of drones search an area while reporting back to a central node. This swarm approach is able to cover more area faster and implements a centralized architecture (Chen et al., 2020). Additionally, fast collision avoidance is important to prevent equipmental damages. This is typically done with vision, ultrasonic, or infrared sensing built into the UAV (DJI, n.d.).

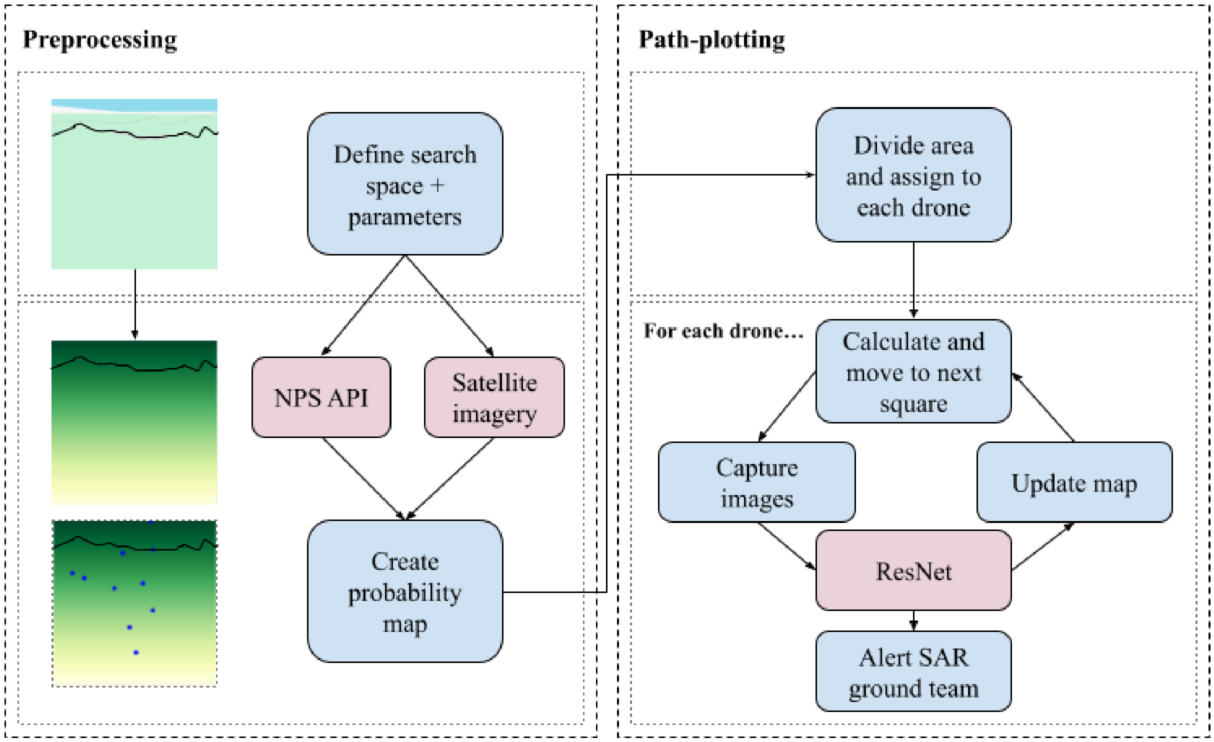
Once a network is chosen, the next step is to consider how the area will be searched. The search area is typically established using the last known point of the target and constructing an area around it. This can be done by using the predicted speed of the target and the time missing to find distance traveled. Alternatively the search area could end at a gate or landmark as the target would likely stop there (Phillips et al., 2014, p. 171). Of course, the first method that comes to mind is brute force: just search the whole area in no specific order; however, we can take advantage of the fact that survivors tend to stay close to certain landmarks and structures.

We can search areas of higher probabilities first to cut down on the time for the operation. It is possible to predict locations of survivors based on the direction of their travel and step length. Additionally, SAR behaviors can be modeled with probability equations to see how the targets have dispersed within a certain time (Liu & Wang, 2017). With the help of probability maps SAR drones can search more important areas first, allowing more people to be found faster. Results from experiments on the effect of terrain on movement of a lost person show that the methods to search an area are highly dependent on the landscape of that area (Hashimoto et al., 2022). However, they didn’t consider the strategies of the person, which can be taken into account with the survivability behavior introduced previously. Lost individuals tend to stick to geographic paths of least resistance, like trails or rivers. Targets tend to travel downhill, unless in mountainous areas where they travel uphill to obtain cell signals (Phillips et al., 2014, pp. 168-169). With this knowledge, we can create a probability map with areas like these trails and rivers having higher weighting.

Once this map is constructed, the drone needs to know which path to take to reach the target in minimal time. This is modeled after the particle swarm optimization (PSO) method, a commonly used multi-UAV algorithm, which optimizes drone position by minimizing an objective function (Belkadi et al., 2015). In this case, the objective function would be the path, as a shorter path results in a shorter time, accomplishing the goal. A study from Lee et al. (2018) shows how factoring in the environment and trying to maximize the efficiency with a particle swarm-type algorithm was highly successful, and considering that they simulated these drones in conditions that were similar to the real world. Again, this paper focused on the effects of the terrain on searching for targets, which can be further investigated by incorporating the targets behavior and now, the idea of minimizing the path is also introduced. Now that a probability map can be constructed and the most efficient path can be chosen, a computer needs to be able to implement these tasks, so an algorithm is necessary. Khosravi et al. (2022) published a pseudocode algorithm that used a probability map to detect signs of fire in an area. They used a Residual Network (ResNet) to identify signs of smoke, sparks, or fire, which would then communicate with the parent algorithm and react accordingly. This could be implemented for SAR by using a ResNet that identifies not only the targets, but also signs of a potential target. It is also possible to narrow the search area by finding a certain number of potential targets and then finding the target. Humans can easily discern that if there is a discarded shoe somewhere, the owner might be nearby, but for a drone, it might not be so obvious. Therefore, incorporating a machine learning residual network into our algorithm would help the SAR area greatly decrease as time went by and make it faster to find the final targets (Thoreau & Wilson, 2021). Utilizing probability maps, path plotting with particle swarm optimization, ResNets, and a multi-UAV system, SAR efficiency could greatly increase with this novel research.

Research Plan

Our goal is to develop a novel algorithm for faster SAR using a multi-UAV swarm with the knowledge of survival behavior models. This would involve creating an accurate probability map based on our research, a path-plotting algorithm which is then used to plot a sub-optimal search path, and incorporating ResNets like Meta's Detectaron2 (Facebook Research, 2023) or other available models (Arora, 2021; Arora, 2023; Sambolek & Ivasic-Kos, 2021) to identify potential targets during flight. This project will be simulated using the DJI flight simulator and is feasible as shown by Arora (2021) who incorporated a different algorithm for SAR using the DJI flight simulator. A flowchart of the steps taken is shown on the next page.



There are two main components, one, the creation of a probability map from our designated search space utilizing survival behavior models and two, the path plotting algorithm utilizing the probability map. The rectangular search space is defined by two coordinates, the lower left corner and upper right corner. This search region is divided into square units, each of which is as large as the drone camera coverage. Since people tend to be closer to trails, we can utilize the National Park Service API (NPS, 2023) to get the coordinates of all the trails in the search space. We can do something similar with rivers, campgrounds, and other areas where people are expected to be (Phillips et al., 2014). These regions are assigned a higher probability than other regions. Additionally, if overhead satellite imagery data is available, we can utilize machine learning image classification to identify possible targets preemptively (Thoreau & Wilson, 2021; Thoreau, 2021). We can see this in our diagram where the region around the trail has higher probabilities, indicated by darker colors, than regions farther from the trail.

Now we can split the search space among the drones and assign each drone a region and starting point such that each region has about the same amount of high probability areas (Phillips et al., 2014, p. 171). Next we have the path plotting algorithm where the drone uses the probability map to make an informed decision locally on where to go next. It travels to a neighboring square unit inside its assigned region decided by the path plotting algorithm and then captures an image. This image is processed using an image ResNet which provides data on if a target is in the unit. If a target is detected, the search team is informed and the probability is updated to 0 so the region does not have to be searched again. The ground search team will find something if the target is there. However, if it is decided the unit does not contain the target, the probability is updated by the following formula, assuming the former unit probability is p and the false negative rate is r_n, and the false positive rate is r_p:

$$p_{new} = \frac{pr_n}{pr_n + (1-p)(1-r_p)}$$

The path plotting algorithms being tested are:

1. Simple brute force: Search without regards to probability map.
2. Naive search: Search areas in order of probability, irrespective of how far they are away from each other. This could potentially be worse than brute force due to wasted time of traveling and redundant searching.
3. From the current point travel to the highest probability neighbor. This would work well if only one connected high probability search region; however, not the best if high probability regions are scattered.
4. Travel to the best square weighted by distance using probability / distance: Traveling to a region has costs. Want to search close but slightly lower probability regions over farther higher probability regions.

In general, the ones that visit the higher probability areas faster are better. This helps the drones search only relevant areas while finding the shortest path to where the target is most likely to be, which allows the drone to look in as few places as possible. The targets are placed according to where we expect them based on the probability map and survival behavior models. When simulated, the drone would also have collision avoidance implemented as standard with UAV missions.

So far we have created a 2D simulator which can generate a random probability map and place targets randomly with the probability distribution provided. It also allows for the simulated drones to travel across the grid according to a set of instructions. In the future we would continue our research with the following steps.

- 2/3/2024: Make an accurate probability map of a defined region and distribute the targets based on this map. This map is what our algorithm will be run on.
- 3/16/24: Test algorithms with a 2D simulator that we made and officially establish the best algorithm. This is evaluated by maximizing the area under the curve of a graph with time on the x-axis and people found on the y-axis. The faster a person is found, the greater the area. The basic search ignoring probability map would have a linear graph.
- 4/20/24: Simulator flies one drone with basic algorithm (full search) using ResNets and object avoidance
- 5/11/24: Once the simulator has been configured, run one drone with our algorithm design and test to see if it is faster than the basic algorithm.
- 6/15/24: Finally, implement the multi UAV swarm (group of drones that connect to the central node) on the simulator with our algorithm design. Final code will be available on GitHub.

We will test and evaluate this project on our own computers with the 2D simulator designed, but once we have established the algorithm, we would like to test with a proper flight simulator. The DJI flight simulator runs on a Windows device which we own. As we are working as a group of two, we have a GitHub set up so that both partners can contribute the code, even if only one can run it with the provided equipment. We both will work on different parts of the algorithm, and put it together at the end to get our final design. Another way we are facilitating collaboration is by checking the other person's work. For the writing components we split it up so that each partner has a similar share, and when we finish, the other partner proofreads. Then, we both edit together. This way, the piece can be seen by two perspectives, and the collaboration will foster more innovative thinking.

To implement this project, we first need a mentor that not only has experience in drone simulations and simulation software. Additionally, our everyday computers can barely handle the softwares we have tried so far, so in order to have optimal testing, we need powerful GPU processing speed and a compatible operating system. DJI Flight Simulator (our preferred option) runs on Windows 11. Although we have a Windows computer, we don’t think it will be able to support our multi-drone swarm in its simulations and will end up being slow. We are fortunate to have access to so many databases through our school, but even still, we ran into many issues with papers we could not access. We would love to have access to MIT’s database of articles and data sets for our testing as well. Funding will go towards purchasing a GPU and connector to aid in simulation as simulators tend to be computationally intensive.

Item	Amount	Cost
GPU Coprocessor- AMD Radeon RX 6700 XT	1	$599
External egpu enclosure - Sonnet eGPU Breakaway Box 750ex - External GPU Chassis	1	$299

Some possible issues we could encounter when implementing our idea include:

1. The area is too large and the range of the central node cannot cover it
    a. The centralized approach that we chose to use is helpful as it is cost efficient, but it has its restrictions. The central node only has a limited range (depending on which one), so an extremely large search area could pose some issues. One solution is to have two central nodes and split the area into two sections, but another solution is to use another network. With the Multi Group Swarm Ad Hoc Network, the central node connects to a swarm of drones. This is helpful because the swarm of drones can communicate together and increase the range. Although the central node restriction is technically still present, since it extends to a swarm of drones, it's much less pressing.
2. Drone Battery life
    a. There is a possibility that the SAR mission will take a long enough time where the drones will run out of battery and cannot continue the mission. One option is to use more drones for efficiency (while keeping the same algorithm). We could also look into optimizing the algorithm by adding more information to the probability map, like prioritizing areas of equal probability. For example, if there is equal probability that the target is in a cave or near a river, but you know it's cold outside, the target is more likely to be in the cave.
3. There is no “highest probability area” due to lack of data provided by the NPS in the given region and the drone doesn’t know where to start
    a. This was slightly touched on in the previous issue, but if the drones initial probability map isn’t enough information, we can use the Google Maps API to

help enhance our probability map. The Google Maps API would be able to provide satellite imagery which we could use to detect trails, areas of low ground, and rivers if this data isn't available elsewhere with the help of a computer vision machine learning model. This can be trained on the survival behavior models and further enhance the accuracy of the probability map.

Personal Interest

Both of us are passionate about mathematics and computer science, taking as many electives as we can in those areas and participating in many competitions. We have undertaken coding projects before, especially in Python (which we are both very comfortable with), but we don't have much experience with UAVs or SAR. We decided to pursue research in SAR because as we have visited national parks and mountains in the past, we know how important it is to stay safe in the wilderness, especially due to lack of cell signal. Although there are already many precautions set in place, it is still possible for someone to get lost, and we would never want someone's family to experience the loss because of this. That's why we decided to see how we can optimize the protocols that already exist, to eliminate as many losses as possible. We also think it's interesting how so many fields can intersect, not only with math or science, but also psychology. Before this study, we would never have realized how important it is to understand the mind of a target when they are lost, to understand where they would go in order to effectively search for them. We are both very proud of this research, and we hope that it can provide new knowledge and help save lives in the future!

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