Implementation of Survivor Detection Strategies Using Drones

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Abstract

Survivors stranded during floods tend to seek refuge on dry land. It is important to search for these survivors and help them reach safety as quickly as possible. The terrain in such situations however, is heavily damaged and restricts the movement of emergency personnel towards these survivors. Therefore, it is advantageous to utilize Unmanned Aerial Vehicles (UAVs) in cooperation with on-ground first-responders to aid search and rescue efforts.

In this article we demonstrate an implementation and improvement of the weight-based path planning algorithm using an off-the-shelf UAV. The coordinates of the survivor and their heading is reported by an on-ground observer to the UAV to generate a weighted map of the surroundings for exploration. Each coordinate in the map is assigned a weight which dictates the priority of exploration. These waypoints are then sorted on the basis of their weights to arrive at an ordered list for exploration by the UAV.

We developed the model in MATLAB, followed by prototyping on Robot Operating System (ROS) using a 3DR Iris Quadcopter. We tested the model on an off-the-shelf UAV by utilizing the MAVROS and MAVLINK capabilities of ROS. During the implementation of the algorithm on the UAV, several additional factors such as unreliable GPS signals and limited field of view which could effect the performance of the model were in effect, despite which the algorithm performed fairly well.

We compared our model with conventional algorithms described in the literature, and showed that our implementation outperforms them.

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1. Introduction

Floods are one of the most devastating natural disasters, causing significant damage to property and human life. In order to speed up search and rescue efforts in the aftermath of such situations, a number of technological solutions have been proposed [1], [2]. Given their rapid commercialization, Unmanned Aerial Vehicles (UAVs) in recent years are becoming a viable option [3], [4], [5] serving as an aid in search and rescue operations in the aftermath of such floods.

Conventional planning algorithms, such as lawn-mower pattern search, utilized to carry out search and rescue make no use of prior information gathered by on-site emergency personnel. In realistic scenarios however, this information is of vital importance, especially while predicting a survivor’s position in fast moving flood waters.

In this article, we demonstrate a modification and implementation of a previously proposed "weight-based" model [6], where a survivor’s location and heading, as observed by an on-ground emergency personnel, is utilized to generate a probabilistic map of the survivor’s location.

1.1. Previous Work

Conventional planning algorithms for search and rescue, such as lawn-mower exploration, do not make use of any prior information as reported by on-ground observers. The Weight-Based algorithm [6] however, utilizes the survivor’s coordinates and heading to generate a prioritized list of coordinates for exploration.

Referencing Figure 1.3, the direction of the survivor’s heading receives the highest priority of exploration, the quadrants on either side receiving the next priority and the direction opposite to the heading receives the last priority.

We deployed the algorithm described, initially on MATLAB to test the veracity of the model [6]. In order to test the model’s capabilities against a standard lawn-mower search pattern, we carried out Monte-Carlo testing [6] using a set of 10 parameters, tabulated below.
From the Monte-Carlo simulations performed in [6], we showed that in a simulation only environment, the Weight-Based method outperformed the standard lawn-mower and a weighted lawn-mower search methods. The results from [6] are shown Figure 1.1 and Figure 1.2.

![Figure 1: Number of Simulations vs Average Decision Making Time for Search Algorithms](image)

In this article, we build upon this previous work [6] and show that our model
outperforms the conventional lawn-mower search both in ROS simulations and in real-life testing using an off-the-shelf UAV.

The MATLAB environment was also used to perform the Monte-Carlo simulations presented under Section 1.1.1, to compare the decision making time and the time to reach the survivor against two existing search algorithms, the lawn-mower method and the probability based search.

We then tested the model on Robot Operating System (ROS) in order to test the model’s viability and robustness. After extensive testing in simulations we tested the model on an off-the-shelf UAV using ROS’ compatibility with the PX4 flight controller hardware.

We utilized the MAVROS capability of MAVLINK to communicate with the PX4 on-board the UAV. The physical set-up to carry out testing has been discussed in detail under Section 1.3.

2. Modified Weight-Based Exploration

The “weight-based” algorithm is a novel path-planning algorithm that generates a prioritized map of the survivor’s possible location. This prob-
A probabilistic model generates a prioritized list of waypoints by differentially assigning weights to each waypoint, depending on their location relative to the survivor’s heading.

In Figure 1.1 above:

1. The **green** path represents the lawn-mower trajectory of the UAV before being called by the observer to a survivor’s last known coordinates.
2. The **red** dot and accompanying blue dotted line represents the survivor’s last known coordinates and direction as relayed to the UAV by the survivor.
3. The **blue** path represents the trajectory of the UAV after the weight-based exploration has been triggered.
4. The **numbers (1, 2, 3, 4)** at the corner of each quadrant represents their exploration priority during the weighted exploration.
2.1. Model Description

In the model, we assume that the observer has a fixed radius of surveillance. If a survivor enters this surveillance region, the observer reports the survivor’s information to the UAV. This information reported by the observer contains the survivor’s coordinates and their heading.

Once the UAV receives this information, it breaks away from the lawn-mower pattern of search and heads over to the coordinates of the survivor as reported by the observer.

The UAV utilizes the survivor’s information to generate the aforementioned weighted map of the surroundings. This approach is probabilistic in nature given that coordinates are assigned weights relative to their bearing from the survivor’s reported direction.

The weighted exploration utilizes the observer’s information to create a prioritized list of waypoints, based on the following order:

1. The survivor’s last known coordinates receive the highest weight, ensuring that the UAV explores it first, before moving on to the rest of the coordinates.
2. Coordinates that lie along the direction of the survivor’s heading receive the highest weights.
3. The directions on either side of the survivor’s heading have equal priority of exploration. If the heading is equally aligned to adjacent quadrants, we assume a higher priority to the left quadrant.
4. Coordinates lying in direction opposite to the survivor’s heading receive the lowest weights.

This iterative differential assignment of weights to the coordinates based on their proximity to the survivor’s location and heading is utilized to rank them and arrive at an ordered list of waypoints, where the waypoints with the highest weights are explored first by the UAV, as they are the most probable locations where the survivor might be present.

This ordered list is conveyed to the UAV for sequential exploration of the region. We utilize the MAVROS capability of ROS to achieve a sequential delivery of ordered waypoints to the UAV.
2.1.1. **Weight Calculation**

In [6] the weights assigned to the quadrants were calculated heuristically. In large environments, a condition may arise when equal weights may be assigned to coordinates in two different quadrants. Such a condition, as observed in simulations as well, causes erratic movement of the UAV while moving from one waypoint to another.

To prevent such a condition from arising, we devise a set of equations which take into consideration the size of the environment and the survivor’s position to generate a set of weights which will be used during iterative assignment to the coordinates.

Let the weights assigned to the four quadrants be denoted as $W_1$, $W_2$, $W_3$, $W_4$ and $W_5$ be the weight assigned to the survivor’s last reported coordinate.

In accordance to priority of quadrants described in the Model Description in Section 1.1.3:

1. Let $W_1$ be the weight assigned to the quadrant along the survivor’s direction of heading.
2. Let $W_2$ and $W_3$ be the weights assigned to quadrants on left and right of the survivor’s heading respectively.
3. Let $W_4$ be the weight assigned to the direction opposite to the survivor’s heading.
4. Let $W_5$ be the weight assigned to the survivor’s last known coordinates.

Given these conditions, assuming the heading to be equal alignment of the heading to either adjacent quadrants, the order of weights is as follows:

$$W_1 > W_2 > W_3 > W_4 \quad (1)$$

We define a set for each quadrant, spanning the least possible weight ($W_i$) to the maximum possible weight attained by a coordinate lying in that coordinate ($W_{i \text{ max}}$).

Such a set can be denoted as:

$$[W_i, W_{i \text{ max}}]$$

$W_{i \text{ max}}$ can be defined as:

$$W_{i \text{ max}} = N \times W_i$$
Here, $N$ is the maximum number of iterations required to move from the survivor’s coordinates to the boundary of the environment ($X_e, Y_e$). It can be calculated as:

$$N = X_e - X_s$$

or

$$N = Y_e - Y_s$$

whichever is greater.

From the inequality (1), the necessary condition to prevent common weights among quadrants is:

$$W_i > W_{(i-1)} \text{ max}$$

(2)

The minimum condition for (2) to be satisfied, assuming $W_i$ to be integers, is:

$$W_i = W_{(i-1)} \text{ max} + 1$$

(3)

From (1) and (2) we arrive at the following set of equations for the corresponding weights:

$$W_1 = ((W_4N^3) + N + N^2 + N^3)$$

(4)

$$W_2 = (W_1 - N)/N$$

(5)

$$W_3 = ((W_1 - N) - N^2)/N^2$$

(6)

$$W_5 = ((W_1N) + 1)$$

(7)

Equation (3) assigns a weight to the survivor’s coordinate that is greater than the highest possible weight assigned along the survivor’s heading.

Here, $W_4$, the weight in the direction opposite to the survivor’s heading, is assumed to be 1, the lowest non-negative integer value that can be assigned as a weight.

In accordance with equation (4), (5), (6), and (7) a color gradient can be observed across quadrants due to differential assignment of the weights.

This map, of differentially weighted coordinates, is used to prioritize and generate a list of waypoints used by the UAV for path-planning in the environment. Figure 1.5 represents the exploration map after prioritization.
Figure 4: Weight Density Across the Simulation Environment

Figure 5: Priority of Exploration of Waypoints
3. Simulations

Before the implementation of the algorithm on the UAV, we tested the model on MATLAB in [6], followed by simulations on Robot Operating System (ROS), using a standard 3DR Iris Quadcopter. Both of these simulations environments are discussed in the sections below.

### 3.1. MATLAB Simulations

The initial simulations to test the veracity of the algorithm were performed on MATLAB [6]. The environment on MATLAB is shown in a series of sub-figures in Figure 1.6.

The environment shown in Figure 1.4 was also used to arrive at the Monte-Carlo simulation results as presented in Section 1.1.1.

In the 600 m x 600 m MATLAB environment shown in Figure 1.6:

1. Multiple observers are assumed, represented by **blue** circles. The observers are assumed to have a fixed radius of observation.
2. The UAV is described as a **pink** box with a trailing pink dotted trajectory.
3. The survivor is represented by a **red** asterisk, with a red trajectory.

![Figure 6: MATLAB Simulations of Model](image)

In Figure 1.4:

1. In the **first** sub-figure, the UAV is initially executing the lawn-mower pattern of search and the survivor is set to a random trajectory.
2. In the **second** sub-figure, the survivor breaches the radius of one of the observers. The UAV breaks away from lawn-mower search and begins executing the weight-based search, utilizing the heading and coordinates of the survivor.
3. Through the weight-based search, the UAV eventually catches up to the survivor in the third sub-figure.

For the Monte-Carlo simulations on MATLAB, the variables in Table 1.1 were considered, including varying number of observers with randomized positions, and variable survivor trajectories as well.

3.2. Robot Operating System Simulations

The model was ported from MATLAB to ROS prior to testing on hardware, given the compatibility of the hardware systems with the ROS framework. The code was written primarily in C++. As mentioned, in order to communicate with the Pixhawk PX4 flight-controller on-board the simulated Iris Drone and the physical drone, the MAVLINK and MAVROS capabilities of ROS were used.

![Figure 7: ROS Environment](image)

A 3DR Iris Quadcopter was used to prototype the model on ROS, with an on-board PX4 controller. This simulation configuration was selected because of the semblance to our real drone, ensuring compatibility of the ROS and C++ modules written for the two systems.
Figure 1.5 represents the prototyping ROS environment. The environment is assumed to be 20 m x 20 m. The Iris Quadcopter is located at the top left. A single observer is assumed, located at the (10, 10) coordinate of the environment, represented by a ClearPath Husky.

During initialization of the ROS environment the controller generates a local coordinate system with the UAV localized at the origin. We utilize this local coordinate system to generate the waypoints for navigation and for the UAV’s path planning.

ROS also provides an interface to debug the model prior to hardware testing, through tools such as RViz, rqt_graph and ROS Bags. In order to log data such as the positions of the UAV and the survivor for visualizations, we run nodes to subscribe to these parameters.

4. Implementation

For the implementation of the model on the UAV, as mentioned, we use the MAVLINK and MAVROS capabilities of ROS to communicate with the on-board flight computer. In our case the on-board flight computer is a Pixhawk PX4 board. The physical setup is as shown in Figure 1.8.

Figure 8: Hardware setup for physical testing
The PX4 enables interfacing with the ROS code that runs the UAV during simulations, therefore ensuring similar performance and compatibility with the C++ code.

Figure 9: ROS Graph of interacting nodes during simulation

Figure 1.9 represents the ROS Graph, which can be used to visualize the various nodes transacting topics amongst each other during the ROS simulation.

5. Results

We use the time taken by the UAV to find the survivor as a metric of each model’s performance. We assume an environment of 20 m x 20 m for the ROS simulations and a testing environment of 10 m x 10 m for physical testing. The variation in the UAV’s X, Y and Z coordinates are presented as well. The survivor velocity $V_s$ is set at 0.6 m/s for simulation and 0.3 m/s for physical testing.

5.1. ROS Results

5.1.1. Weight-Based Exploration

The survivor is assumed to move linearly with a velocity $V_s = 0.6$ m/s. The total time taken for the weight-based survivor search to conclude is 213 seconds.
5.1.2. Lawn-Mower Exploration

The survivor is assumed to move linearly with a velocity $V_s = 0.6 \text{ m/s}$. The total time taken for the survivor search to conclude is 669 seconds.
From the simulations, it is apparent that the search time of the weight-based exploration outperforms the search time of the lawn-mower exploration by nearly 215%.
We have tabulated the search time for the two exploration strategies with varying survivor velocities \((V_s = 0.6 \text{ m/s and } V_s = 0.3 \text{ m/s})\) and two different environment sizes \((20 \text{ m x } 20 \text{ m and } 18 \text{ m x } 18 \text{ m})\). These results are presented in Table 1.2.

| Environment Size \((m^2)\) | \(V_s \text{ (m/s)}\) | \(T_L \text{ (s)}\) | \(T_W \text{ (s)}\) |
|-----------------------------|----------------------|------------------|------------------|
| 18 x 18                     | 0.6                  | 624              | 173              |
| 20 x 20                     | 0.6                  | 669              | 213              |
| 18 x 18                     | 0.3                  | 600              | 63               |
| 20 x 20                     | 0.3                  | 663              | 66               |

\(V_s\) - Survivor Velocity  
\(T_L\) - Time taken to find survivor using lawn-mower search  
\(T_W\) - Time taken to find survivor using weight-based search

As evident from Table 1.2, our model comprising of weight-based exploration clearly outperforms, by nearly an order of magnitude, the standard lawn-mower search pattern, considering varied environment sizes and survivor velocities.

5.2. Implementation Results

We carried out the physical tests in a 10 m x 10 m area. As described under Section 1.3, we use an off-the-shelf UAV with a 6000 mAh on-board battery. The Pixhawk PX4 flight computer on-board runs a MAVROS node that communicates with the on-ground system that runs the ROS model.

The virtual survivor is a simple mathematical model which moves linearly with a velocity of 0.3 m/s. It is assumed to originate from the observer’s position at \((5, 5)\) in the 10 m x 10 m environment.

Each sub-section below has the X-Y projection accompanying the 3D trajectory of the prototyping environment to provide a better perspective of the respective search patterns.

5.2.1. Weight-Based Exploration

As observed from Figure 1.16, 1.17 and 1.18, the UAV successfully manages to execute the weight-based exploration and catches up to the survivor and returns back to the start coordinates with this information.
The UAV takes 149 seconds to complete this operation. In the following section we compute the search time with the standard lawn-mower search pattern and compare the results of the two methods.

5.2.2. **Lawn-Mower Exploration**

For lawn-mower exploration as well, a 10 m x 10 m area is used for testing. The survivor is located at (5, 5) in the local coordinate system spawned by the UAV during initializing.

As seen from the Figure 1.19, 1.20 and 1.21, the lawn-mower search in physical testing takes 261 seconds to detect the survivor, in comparison to the 149 seconds taken by the weight-based exploration, an improvement of 75%.
During the physical testing, fluctuations in the PX4 on-board the UAV were observed leading to erratic patterns in Figure 1.17 and Figure 1.20. In addition, strong winds caused some amount of deviation from the prescribed trajectory of the UAV.

![Figure 19: Trajectory and X-Y Projection of UAV and Survivor](image)

**Figure 19**: Trajectory and X-Y Projection of UAV and Survivor

![Figure 20: Variation in X, Y, Z Coordinates of Survivor](image)

**Figure 20**: Variation in X, Y, Z Coordinates of Survivor $V_s = 0.3$ m/s

![Figure 21: Variation in X, Y, Z Coordinates of UAV](image)

**Figure 21**: Variation in X, Y, Z Coordinates of UAV

### 6. Conclusion

In this article, we present an implementation and improvement of a previously described "weight-based" exploration method. We implemented the model on ROS and an off-the-shelf UAV.
In comparison to the standard lawn-mower pattern of search the weight-based search, both in simulation and physical testing, demonstrates a significant improvement to the time taken to search for a survivor.

The model described is agnostic to the number of agents and survivors. Our future work involves deploying this model on multiple agents to investigate large swaths of land for survivors, in collaboration with on-ground personnel.

7. Future Work

The physical tests detailed in the previous sections were restricted to controlled environments. Future tests will be conducted at the Indian Institute of Science's Challakere Campus, given the semblance to a realistic environment where such a solution would be deployed to aid first-responders.

In this article, we’ve assumed a virtual survivor for the UAV to track; However, we are currently developing a novel computer-vision pipeline trained on images of humans from an overhead camera. This pipeline would be integrated into the current model and will be deployed to detect human survivors autonomously using an on-board camera.

In the future, we aim to deploy this algorithm on a swarm of UAVs, which, along-with human counterparts would have the capability to investigate large swaths of flooded area, effectively speeding up the search for survivors.

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