Realistic Aircraft Crash Survivor Path Estimation via A-Star Search Algorithm and Gradient Descent

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***Abstract*—In this work, we introduce a novel method of generating a realistic, human-like path-to-safety prediction for aircraft crash survivors using heuristic-based decision-making A-Star algorithm and Gradient Descent (GD). The rescue of survivors of a crash, that occurs in a rural or wilderness setting, is filled with uncertainty regarding the movement of survivors from the point of the crash to the point of rescue. Our study analyzes the movements of aircraft crash survivors using circuit theory to model connectivity in heterogeneous landscapes with Circuitscape and QGIS software. Here, given possible points on a terrain map, Circuitscape will generate all possible current connections between them. A-Star search algorithm and GD is then applied to find the most human-like path from the connections. While the least-cost path can also find the shortest route, it requires a full geographic knowledge of the interlying region between start and end points. However, the crash survivor might not have access to such knowledge. By integrating A-Star search algorithm and GD, combined with Circuitscape preprocessing tool, our method successfully models realistic movement patterns throughout the survivors journey. This will reduce rescue time for crash survivors.**

***Index Terms*—A-star search algorithm, gradient descent, circuitscape, path finding, current maps.**

I. Introduction

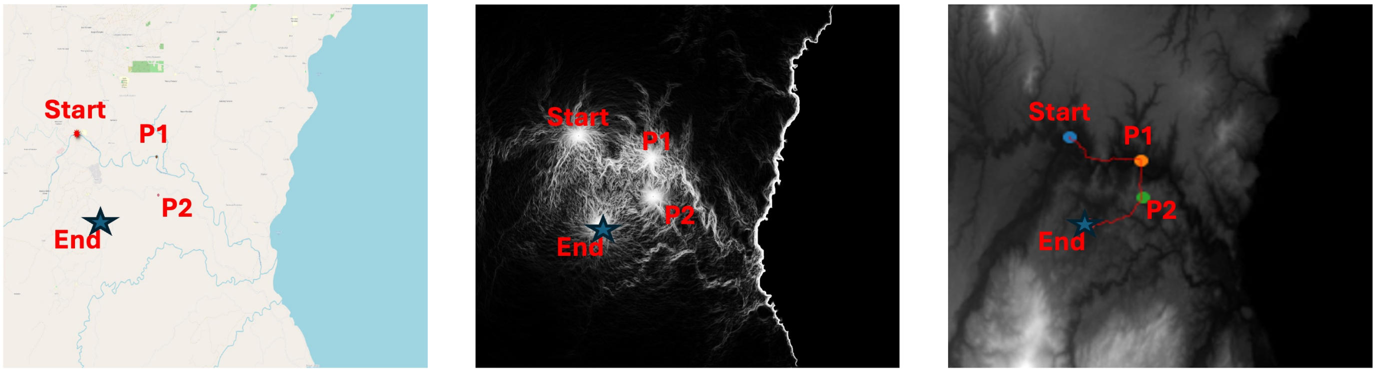
Path estimation and finding in signal processing is often referred to the study of techniques used to determine the trajectory of a signal in a given system or environment. Predicting the probability of signal outage [1] in a specific path and at some distance is an example of path estimation in wireless communication. Similarly, path-finding is a broader concept that involves determining the most efficient route between two points at some distance from each other, often focusing on the shortest or least-cost path [2]. These techniques have been widely applied in fields such as robotics, autonomous navigation, and geographic information systems (GIS) [3].

In warfare and military operations, service personnel face various risks, including aircraft or maritime accidents that leave them stranded in unfamiliar and remote environments with no access to wireless communication [4]. In such situations, survivors must navigate difficult terrain to reach a safe zone as quickly as possible. However, without proper tools for navigation and communication, their movement remains unpredictable. This uncertainty creates a significant challenge for search-and-rescue teams, as locating survivors after identifying the crash site becomes highly complex. Traditional search methods rely on approximations and historical data, but these approaches often fail to account for realistic human decision-making in survival scenarios.

The application of least-cost path analysis to find the shortest path between two points relies on multiple factors and would be similar to a reinforcement learning task [5]. First, it considers the spatial cost associated with traversing a landscape, such as elevation changes, obstacles, and land cover types. Second, it assumes that the traveler follows an optimal decision-making process to minimize effort or energy expenditure. While this approach is effective for calculating efficient routes in structured environments, it often fails to account for the cognitive and behavioral aspects of human navigation. In survival situations, individuals may prioritize accessibility, visibility, or familiarity over the shortest possible distance. Additionally, unpredictable environmental conditions, such as weather changes or natural barriers, can influence route selection, making traditional least-cost path methods inadequate for modeling human movement in emergency scenarios.

To address this problem, our study leverages heuristic-based path-finding methods to predict the movement of crash survivors in wilderness. We propose a novel approach that integrates Circuitscape [6], [7], a circuit theory-based tool for modeling connectivity in heterogeneous terrains, with the A-Star (A^*) search algorithm [8], [9] and Gradient Descent (GD) [10] to estimate the most probable paths taken by survivors. In Fig.2, we demonstrate the steps of creating the current maps to implementing A^* search algorithm to follow the path of a crash survivor. Unlike conventional least-cost path methods, which prioritize distance or energy efficiency, our approach incorporates environmental factors and human behavior tendencies. By combining circuit-based connectivity modeling with heuristic path-finding, our method aims to generate more realistic and human-like movement predictions, enhancing search-and-rescue operations.

The rest of the paper is organized as follows: Section II delves into related works and their method of path-finding. In Section III, discuss our implementation using A-Star algorithm and Gradient Descent. Afterwords, in Section IV, we present the results of testing our method on various maps from aircraft crash survivors.



(a) (b) (c)

Fig. 1: **Path Finding Complete Process via A* Algorithm**: The full process of finding the possible paths for a crash survivor. (a) Is the original map with the point of crash, labeled as $Start$ indicating the crash site, End as the point of rescue, and points of movement labeled from $P1$ and $P2$. (b) The current map generated using Circuitscape software and (c) our A-Star based path estimation method.

II. Related Work

In this section, we discuss two widely used approaches to study and estimate a path in archaeology: Circuitscape, a circuit theory-based software to model connectivity in heterogeneous landscape and the Least-Cost Path (LCP) method, which computes an optimal path based on a predefined cost function.

A. Circuitscape

Circuit theory analysis is a fundamental tool in electrical engineering, often used to analyze current flow in a network of resistors, capacitors, and other electrical components [11]. The governing principle behind this analysis is Ohm's Law:

$$I = \frac{V}{R} \tag{1}$$

where I represents the current, V denotes the voltage, and R is the resistance of the circuit. This foundational equation extends beyond electrical circuits and has been successfully applied to spatial modeling in ecology and geographical studies [12].

Circuitscape, an open-source software written in Julia, utilizes principles from circuit theory to model connectivity in heterogeneous landscapes [7]. Instead of electrical resistances, Circuitscape assigns resistance values to different terrain types based on landscape features derived from satellite imagery processed in software such as QGIS [13]. By interpreting terrain as an electrical network, Circuitscape calculates the effective resistances and current flow between points, which aids in modeling how entities, such as animals or humans, traverse an environment [14].

To execute a Circuitscape analysis, the software requires an input raster map with resistance values and a set of focal nodes, which represent start and target points in the terrain [15]. The program offers various connectivity modes: (1) pairwise mode, which calculates resistance between predefined pairs of points, (2) advanced mode, where connectivity is determined based on a broader network, and (3) one-to-all mode, where a single point is used as a source, and current is spread to all other locations.

Fig. 1b illustrates an example where Circuitscape generates a current flow map given an initial crash point and actual points of movement from a crash survivor. By treating the landscape as an electrical circuit, Circuitscape enables a probabilistic assessment of movement routes, which serves as the input for our A* path search algorithm and GD.

B. Least-Cost Path (LCP) Estimation

The Least-Cost Path (LCP) method is widely used in GIS and environmental modeling to determine the optimal path between two points by minimizing an accumulated cost function [16]. This approach is particularly useful in terrain analysis, where different regions impose varying traversal difficulties. Given a cost surface $C(x, y)$ that assigns a traversal cost to each spatial location (x, y), the total cost of a path $\mathcal{P}$ from the source s to the destination d is given by:

$$C(\mathcal{P}) = \sum_{i=1}^{n-1} c(x_i, x_{i+1}), \tag{2}$$

where $c(x_i, x_{i+1})$ represents the transition cost between consecutive locations along the path. The optimal path $\mathcal{P}^*$ is then found by solving:

$$\mathcal{P}^* = \arg\min_{\mathcal{P}} C(\mathcal{P}). \tag{3}$$

The cost function $c(x_i, x_{i+1})$ can be influenced by several factors, including elevation gradients, terrain roughness, and land cover types [17].

Despite its effectiveness in structured environments, the LCP method has limitations when modeling human movement in complex landscapes. The method assumes that individuals always follow the globally optimal path based on cost minimization, which may not reflect real-world behavior where local decisions and psychological factors influence movement. Additionally, it requires a full geographic knowledge of the interlaying region between start and end points. However, the crash survivor might not have access to such knowledge.

III. Method

We present our method of path-finding in this section. Here, we introduce the novel implementation of A-Star search algorithm and gradient descent-based path estimation to find all possible paths given a crash point and possible end points using circuit maps.

A. Gradient Descent/ Ascent

One approach in a path-finding task is gradient-based optimization [10], [18], which formulates the path as a continuous function and iteratively updates it using numerical methods. This approach is particularly useful when working with continuous cost functions to find the global minimum and when smooth trajectory adjustments are required.

Let $\mathbf{x}(t) \in \mathbb{R}^2$ define a parametric path over time t, where the goal is to minimize an energy function $E(\mathbf{x})$ that encodes the traversal difficulty of the terrain:

$$E(\mathbf{x}) = \int_0^T f(\mathbf{x}(t))dt, \tag{4}$$

where $f(\mathbf{x})$ represents a local cost function that depends on environmental factors such as slope, visibility, and terrain type. The optimal path is obtained by iteratively updating the trajectory using gradient descent algorithm, where the update rule is given by:

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \eta \nabla E(\mathbf{x}_k), \tag{5}$$

where η is the step size or learning rate, and $\nabla E(\mathbf{x}_k)$ represents the gradient of the energy function with respect to the current path estimate $\mathbf{x}_k$. If the negative sing is flipped to a positive sign, the algorithm becomes gradient ascent.

Gradient-based methods are widely used in robotics and physics-based simulations, where smooth trajectories are essential [19]. In our implementation, we perform gradient descent and ascent on the current map. These methods allow for adaptive updates based on local terrain variations, making them more flexible compared to discrete graph-based approaches like LCP.

B. A-Star Search Algorithm

Path-finding algorithms play a crucial role in many applications, from robotics and navigation systems to video game AI and rescue missions. Among them, the A-Star (A*) algorithm stands out due to its ability to find the most optimal path efficiently [20].

A* can be defined as a graph traversal and search algorithm that finds the shortest path between a start node s and a goal node g using a cost function $f(n)$:

$$f(n) = g(n) + h(n) \tag{6}$$

where $g(n)$ represents the actual cost from the start node s to the current node n, and $h(n)$ is the heuristic estimate of the cost from n to the goal node g.

A-Star employs a best-first search strategy by iteratively selecting the node with the lowest $f(n)$. The heuristic function $h(n)$ is commonly chosen as the Euclidean distance:

$$h(n) = \sqrt{(x_n - x_g)^2 + (y_n - y_g)^2} \tag{7}$$

where (x_n, y_n) are the coordinates of the current node and (x_g, y_g) are the coordinates of the goal node.

For path-finding, the current flow map is generated by Circuitscape, A* is then applied to find the most human-like path from the crash point to possible rescue locations. Unlike traditional least-cost path methods, which prioritize purely shortest-distance traversal, A* incorporates terrain resistance and heuristic decision-making. The algorithm follows these steps:

1) **Initialization**: Define the crash site as the start node s and the potential rescue zones as goal nodes g.
2) **Open and Closed Lists**: Maintain an open list of nodes to be evaluated and a closed list of nodes already explored.
3) **Node Expansion**: Select the path to the node with the lowest $f(n)$ from the open list and expand its neighbors.
4) **Cost Calculation**: Compute $g(n)$ based on the resistance values from Circuitscape and update $h(n)$ dynamically.
5) **Path Reconstruction**: Once the goal node is reached, backtrack through the parent nodes to reconstruct the optimal path.

A* improves upon traditional methods such as Dijkstra's algorithm, which searches all nodes indiscriminately [21], and the Least-Cost Path (LCP) method, which ignores human behavior constraints. Unlike gradient-descent-based path-finding, which may converge to local minima, A-Star ensures global optimality by balancing path cost and heuristic estimates. The algorithm then can be refined as:

$$f(n) = g(n) + w \cdot h(n), \quad w > 0 \tag{8}$$

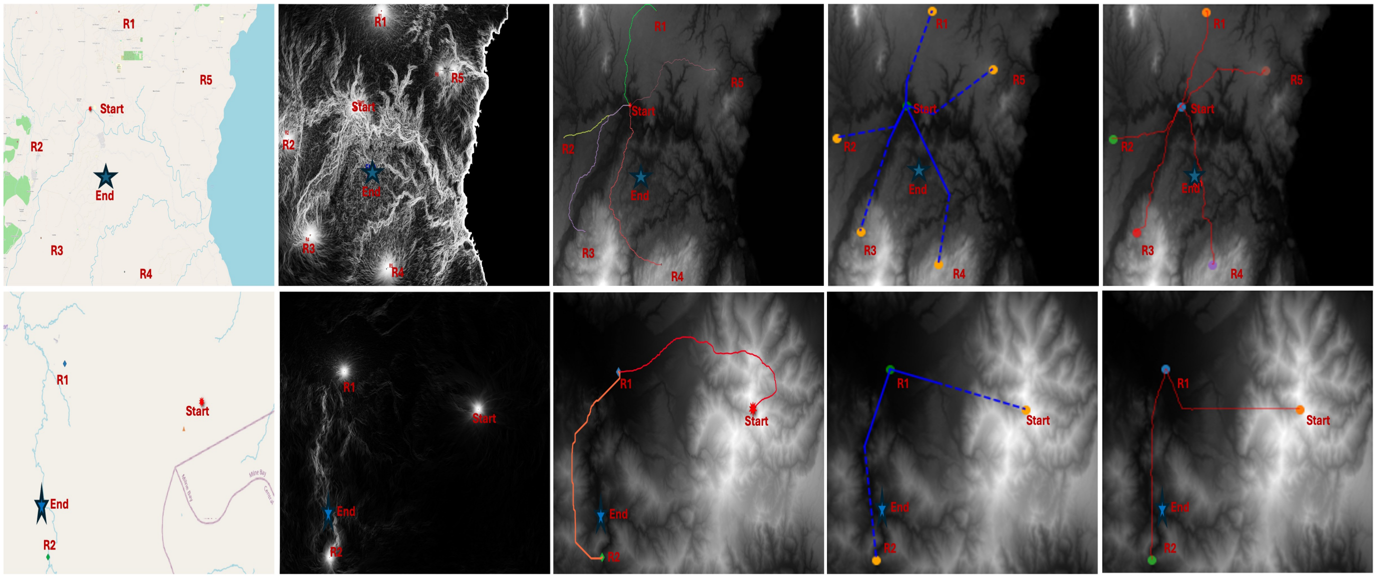
where w is a weighting factor that adjusts heuristic influence, allowing A-Star to adapt to varying terrain complexities.

The time complexity of A-Star is generally $O(b^d)$, where b is the branching factor and d is the depth of the shortest path. The algorithm's efficiency depends on the heuristic function $h(n)$. If $h(n)$ is admissible, A-Star guarantees the optimal solution.

Given its flexibility, A-Star has been used in autonomous navigation, and real-time decision-making systems. In our case, integrating A-Star with Circuitscape provides a realistic prediction of survivor movement, ensuring efficient rescue missions in wilderness.

IV. Experimental Results

In this section, we present the dataset used in this work and establish the evaluation metrics that will form the basis of our



(a) Original Map (b) Current Map (c) LCP (d) GD (e) A* Ours

Fig. 2: **Comparison Graph**: Comparison between the common methods of path finding where (a) is the original map with the points of interest. (b) The current map, (c) Least-Cost path (LCP) method, (d) Gradiant Descent method (GD), and (c) our A-Star based path estimation method. The $Start$ represent the point of crash, $R1$ to $R5$ represent the possible end points, and End represent the point of rescue.

experiments. These metrics are critical, as evaluating human behavior in survival situations is inherently complex. We then discuss the results of our A-Star method in comparison with the Least-Cost Path (LCP) and Gradient Descent (GD) methods.

A. Dataset

The total dataset consists of geographic information from 20 World War II aircraft crash sites. These sites were carefully selected and extracted from a larger World War II crash database. Each site was processed using QGIS to extract relevant raster data, including terrain slope and elevation. The average map size for each site is approximately 50 km by 30 km, providing a detailed spatial representation suitable for analysis.

In our experiments, we evaluate and showcase the performance of our proposed method on nine representative crash sites. These examples were chosen to highlight the robustness and accuracy of our approach across varying terrain conditions and complexities. The remaining sites are reserved for further validation and generalization assessment in future work.

B. Evaluation Metrics

Human behavior in survival situations varies significantly depending on environmental conditions, prior training, and individual instincts. One common survival strategy for crash survivors is to follow water bodies such as streams, rivers, or shorelines. These features often lead to settlements and provide a visible path for potential rescue operations—help signs on a beach, for instance, can enhance visibility. Additionally, in life-threatening scenarios, individuals tend to follow visible signs of human activity, such as roads, trails, or smoke, as they indicate possible human presence [22], [23].

We input the generated maps fro QGIS into the Circuitscape software to generate current maps based on a predefined set of nodes or locations. The crash site in these maps is marked as $Start$, while the actual rescue location is labeled as End.

However, in real-time scenarios, experts and rescuers estimate the likely rescue location based on environmental conditions and external factors such as conflict zones or terrain complexity. To simulate a realistic rescue mission, we randomly selected multiple points of interest and labeled them as R_i, where $i = 1, 3, 4, 5$.

C. Results

To compare the A*, GD, and LCP methods, we analyze 9 survival scenarios. Figure.1 illustrates the placement of these points on the original map. The current map represents the circuit analysis results generated using Circuitscape. A comparative analysis of the Least Cost Path (LCP), and our implementation of Gradient Descent (GD) and the A-Star (A*) search algorithm demonstrates the differences in performance when approximating the optimal rescue route.

Table.I evaluates the models' performance based on the average distance between the generated route and the actual rescue point. Our model demonstrates superior performance in generating a route that closely aligns with the optimal rescue location.

TABLE I: **Average Distance to a Rescue Point:** Comparison between LCP, GD, A-Star (A*) algorithms based on the average distance, in kilometers (km), to the actual point of rescue across 9 cases.

Case	LCP (km)	GD (km)	A* (km)
1	2.764	2.341	**0.585**
2	2.375	1.071	**0.419**
3	3.768	1.517	**0.121**
4	4.355	1.215	**0.911**
5	1.208	0.278	**0.185**
6	0.647	0.759	**0.094**
7	2.447	0.336	**0.290**
8	5.999	1.351	**0.225**
9	5.645	2.534	**1.969**

V. Conclusion

Path-finding plays a crucial role in optimizing rescue missions for crash survivors. In this work, we introduced a novel approach for crash survivor path finding that integrates A-Star search algorithm and Gradient descent with circuit theory that models connectivity in heterogeneous landscapes with terrain maps. Our results demonstrate that this method more accurately mimics human movement compared to traditional approaches such as Least-Cost Path (LCP), making it a promising tool for enhancing search-and-rescue operations.

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