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MULTI-CRITERIA MULTI-AGENT PATH PLANNING IN UNSTRUCTURED OFF-ROAD ENVIRONMENTS

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ABSTRACT

Autonomous ground vehicles have the potential to reduce the risk to Soldiers in unfamiliar, unstructured environments. Unmanned operations in unstructured environments require the ability to guide the vehicles from their starting position to a target position. This paper proposes a framework to plan paths across such unstructured environments using a priori information about the environment as cost criteria into a multi-criteria, multi-agent path planner. The proposed multi-criteria, multi-agent path planner uses a penalty-based A algorithm to plan multiple paths across the unstructured environment and uses entropy weighting for generating weights to calculate a multi-criteria cost with distance, risk, and soil trafficability. The paths generated by the proposed framework provide a better overall performance across the cost criteria and can be used as waypoints to navigate UGVs in off-road environments.*

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1. INTRODUCTION

Off-road vehicles are crucial when it comes to operations in dangerous or hard-to-reach areas. Currently, such missions are generally carried out by a team of human operated vehicles. However, such off-road missions can lead to potentially life-threatening situations, especially when navigating an area with compromised structures or when transporting supplies through an unfamiliar or unfriendly zone. But with the advent of unmanned ground vehicles (UGVs) and the ability to carry out missions without a human driver, this risk to human life can be reduced. A UGV can be provided with path information (including waypoints), which it can use to traverse the environment and complete the mission safely.

Path planning in unstructured environments poses a different set of challenges from such planning in structured, urban environments. First, the unstructured nature of the off-road environments means that, unlike an urban environment, where there are well-defined road networks, an off-road environment lacks such structures. Therefore, barring the obstacles, the whole environment can be used by a moving vehicle. Second, the paths must allow the UGV to navigate the environment safely, requiring a more thorough characterization of the environment than typically associated with road segments in existing routing algorithms. This paper addresses the above-mentioned concerns associated with off-road UGV path planning.

The problem context for this paper is a team of UGVs that starts from a depot and splits into sub-teams along multiple paths to arrive at the same target point (destination). This split could be due to different vehicle capabilities, spreading risk exposure, etc. The paths must be as disjoint as possible with an option to converge in the presence of an environmental constraint like a bridge or a pass, i.e., conditionally disjoint.

To address this problem, this research develops a framework that involves: (1) digitally representing the unstructured environment with multiple characteristics, (2) incorporating multiple criteria in the path planning process, and (3) planning multiple conditionally disjoint paths across an unstructured environment. We use the cell decomposition method for environment representation [38]. Our environment is discretized into a hexagonal grid. The multi-criteria multi-agent path planning is done using a penalty-based A* algorithm, which uses environment properties like soil trafficability and risk along with the distance in a multi-criteria cost function. The cost criteria are weighted objectively using the entropy weighting method.

The rest of the paper is outlined as follows: a literature review of the state-of-the-art in multi-criteria, multi-agent path planning and risk representation approaches in path planning; followed by a description of the multi-criteria, multi-agent path planning problem; the methodology; and lastly, there is a results and discussion section with recommendations for further research.

2. LITERATURE REVIEW

2.1. Path planning

Finding the shortest path between two nodes in a graph is a well-researched area. Dijkstra [1] introduced an algorithm which could find the shortest path between a source point and a target point on a map by minimizing the cost to travel from the start point to any other node, until the target point is found. Hart et al. [2] introduced the A* algorithm, which was able to do the same but much quicker because of the use of a heuristic estimate of the distance from a node to the target. These algorithms led to other algorithms like D* [3], D* lite [4], RRT [5], RRT* [6]. These algorithms are useful when solving the path planning problem for a single cost criterion (usually distance) in a simulated or a highly structured environment. However, to be used in an unstructured case, a path planner should also consider the properties of the environment in a multi-criteria cost function.

2.2. Multi-criteria path planning

There has also been a considerable amount of work in multi-criteria path planning. For off-road environments, a multi-criteria path planning framework should consider terrain characteristics. Cai et al. [34] propose a method to generate paths by minimizing the localization uncertainty, collision risk, and distance to the target. However, it fails to incorporate terrain characteristics (slope and soil property), which may result in paths that may not be traversable. Similarly, Kurzer [27] and Shaikh & Goodrich [30] also omit terrain characteristics. Shen et al. [8] and Yu et. al. [9] consider vehicle properties when generating smooth and traversable paths, but they do not consider terrain characteristics.

Roghanian & Kebira [31], Eklund et al. [32], and Rosita et al. [33] use a multi-criteria Dijkstra's approach for path planning, and Zhao et al. [28] use the Multi-Objective Evolutionary Algorithm (MOEA). However, they present generalizations for structured networks and have not been tested in an unstructured environment. Braun [10] uses an interesting approach to generate a single cost measure by evaluating the actual cost to traverse a link, which is then extrapolated to untraversed edges. This method may not be optimal when considering an environment with varying soil properties and slopes. It also fails to provide an opportunity to prioritize one cost criterion over others in the path planning phase. Pandey et al. [11] and Mollan et al. [29] both use terrain properties in conjunction with a physics-based simulator to ensure path completion. However, these methods only plan single paths.

2.3. Multi-agent path planning

Multi-agent path planning has also received some attention. Dinic [12] proposes an algorithm for finding totally disjoint paths in a network with power estimation. Torrieri [13] proposes the same for communication networks. Van der Zijpp et al. [14] and Lawler [15] both propose a way to determine a set of paths that satisfy a certain set of constraints, but they require all the paths between the start and target points to be determined beforehand. Similarly, k-shortest path algorithms like that proposed in Yen [16] and Eppstein [17] generate a shortest path on a graph and then remove some intermediate nodes from consideration for successive path searches. All of the aforementioned multi-agent path planning algorithms have limitations when it comes to an environment where there are some constraints (bridges, narrow pass, etc.) allowing only one through access between the start and the target, because removing from consideration the intermediate nodes will prevent creation of any other paths, and a single passage for access between the start and the target does not allow disjoint paths. Also, k-shortest paths algorithms require an additional step at the end to check if the alternate paths satisfy the specified constraints [23].

On the other hand, Silver [18] generates collision-free paths for multiple agents from different start points to target points by breaking down the search into multiple single agent searches considering time in discrete steps. Phillips and Likhachev [19] introduce the concept of a safe interval, i.e., a time period with no collision, to plan paths for multiple agents. Sharon et al. [20] also break down the multi-agent path planning problem between different start and target points into a series of single agent searches, and then adds constraints to eliminate the conflicting paths. Andreychuk et al. [21] use both safe interval and conflict-resolution in continuous time. The above papers deal with planning paths for agents with different start and goal points while avoiding collisions. Rouphail et al. [22] plans multiple paths by increasing the length of the links in the shortest paths. Pu et al. [23] extend this approach by using Dijkstra's algorithm with a logarithmic edge-weight increment. Chen et al. [24] also use a similar concept with increasing link weights based on the reliability of the links in the shortest path. Bell [25] generates a hyperpath between a start and a target point in a way that compensates for expected link delays. These multi-agent path planning algorithms are catered to a more structured environment with only one significant cost criteria. Roy et al. [26] divide the planning into two phases, a global plan based on distance, soil properties, and risk which guides the local plan using Model Predictive Control. This approach uses a single global path to guide multiple vehicles by maintaining a specific formation. However, it also exposes all the vehicles to the same degree of risk. So, given the imperfect nature of *a priori* information, it is more desirable to produce multiple paths to overcome this limitation.

2.4. Risk in path planning

Different methods have been used to model risk in path planning. Li et al. [35] and Cai et al. [34] model risk as the probability of conflict with the obstacles in the environment. Iwasa et al. [36] propose to move along the path towards the target while evaluating risk, based on the terrain encountered, and then plan a risk-free return path. Aoude et al. [37] model risk based on intention prediction and threat assessment of other vehicles. However, when planning paths for UGVs on an unfamiliar unstructured terrain, not a lot is known about risk in the environment. Therefore, a way to evaluate and minimize risk based on the known information is necessary. Roy et al. [26] consider the risk of interaction with unfriendly agents and model the area in the line of sight of enemy towers as risky. The elevation data, and coordinates of the enemy towers is used with the MATLAB "viewshed" function to generate risk values. However, the location of the unfriendly agents might not be available or may be incorrect. Roy et al. [26] use a binary risk representation, but the areas deemed risky may need to be travelled anyway (in certain circumstances) and the area deemed safe might have some risk associated with it. So, a more robust approach is required to evaluate and minimize risk in unfamiliar, unstructured terrain.

Table 1 shows the gap in the literature. Thus, a multi-agent, multi-criteria path planning algorithm for an unstructured environment that includes terrain properties in the path planning process and generates distinct paths from a single start to a single target point, which do not expose all the agents to the same risk, is required. These paths should not converge unless constrained by some environmental features (bridges, narrow pass, etc.).

3. PROBLEM DESCRIPTION

We have an unstructured off-road environment, where an agent can move to any position (x,y) as long as it is traversable. To simplify the problem, it has been discretized into a hexagonal grid. The properties associated with the environment (obstacle, elevation, soil trafficability, risk) are mapped to the centroids of each of these hexagons(nodes). Furthermore, an agent moves from the centroid of one hexagon H(x_i, y_i) to the centroid of an adjacent hexagon H(x_j, y_j), i.e., from a node to a neighboring node. Distance between any two adjacent hexagons is the centroid distance (CD). Thus, a series of hexagons have to be traversed in order to move from the depot to a target point in the environment. Each hexagon has a distinct node id (H_i) associated with it. Therefore, the environment can be represented as a set of nodes (N= $[H_1, H_2, ...H_i]$), with the environment properties (H($x_i, y_i, Obstacle_i, Elevation_i, SoilTrafficability_i,$ $Risk_i$)) associated with them. We need to plan $\mid P \mid$ paths (P = $[Path_1, Path_2, ...Path_{|P|}]$) for $\mid P \mid$ agents. Each path (k) can be represented by a series of hexagons ($[H_{start}, H_{k1}, H_{k2}, ...H_{target}]$). These paths should be distinct from one another, so that not all paths are exposed to the same risk. However, they also should have the ability to crossover or intersect in the presence of terrain constraints like a bridge or a narrow pass. The choice of the next node on a path is informed with the help of the multi-criteria cost function.

$$c_{ij} = \Sigma_a (w_a * X_a^{ij}) \tag{1}$$

Where c_{ij} is the cost of travelling from node *i* to node *j*, X_a^{ij} is the value of normalized cost parameter *a* (distance, soil trafficability, or risk), and w_a is the value of weight assigned to the cost parameter *a*.

4. METHODOLOGY

The proposed multi-criteria, multi-agent path planning framework involves: first, discretizing the environment and generating the planning data, which contains the information about the planning environment including the values for the cost criteria across the environment. Second, using the planning

Table 1: Path planning literature.

Literature	Multi-Criteria	Terrain Properties	Unstructured Environment	Multi-Agent	1 Start to 1 Target	Distinct Paths	Environment Constraints
[27],[34],[30]	Y	N	-	N	-	-	-
[8],[9]	Y	N	-	N	-	-	-
[7]	Y	Y	-	N	-	-	-
[31]-[33],[28]	Y	-	N	N	-	-	-
[11],[29]	Y	Y	Y	N	-	-	-
[12]-[17]	N	-	-	Y	Y	Y	N
[18]-[21]	N	-	N	Y	N	-	-
[22]-[25]	N	-	N	Y	Y	Y	-
[26]	Y	Y	Y	N	Y	N	Y
This Paper	Y	Y	Y	Y	Y	Y	Y

data to perform multi-criteria, multi-agent path planning using a penalty-based A* algorithm with a multi-criteria cost function weighted using the entropy method. Therefore, the proposed framework can broadly be divided into two stages as follows.

4.1. Preprocessing

In this stage, the information about the planning environment is used to generate data, which is later used in the path planning stage. The subtasks in the preprocessing stage are: environment representation, risk determination, and planning data generation

a. Environment representation: Barring the non-traversable regions (e.g., water bodies) the whole planning environment can be considered as a pathway, i.e. usable by a moving vehicle. Therefore, the planning environment should be represented in a manner that is able to capture this complexity.

Geisbrecht [38] outlines some popular methods of map representation: cell decomposition and roadmaps. Cell decomposition lays out a grid of a specified shape and size over the planning area, where the center of each grid unit becomes a node in the search graph [38]. Similarly, in the roadmap approach, points are randomly selected from the planning area and are interconnected to form the roadmap [38]. However, because of the abundance of traversable area in the off-road environment, roadmap approaches may leave out significant portions of traversable area, which can then lead to inaccessibility of certain areas or may result in longer paths because of limited connectivity. Moreover, these approaches are inefficient for confined sectors of the map (e.g., narrow pass or bridge) because of the low probability of including a point from such areas in the roadmap [38]. On the other hand, the cell decomposition method is flexible with its cell sizes, which can be fine-tuned to reduce the number of cells (e.g., to increase the execution speed) or increase the detail [38]. Therefore, we have chosen the cell decomposition method to represent our planning environment.

The planning area is represented in the form of a hexagonal grid, where the centroids of the hexagon represent the nodes and each centroid is connected to its six neighbors by links. Hexagons are preferred over rectangles when considering aspects like connectivity or movement paths [46]. Similarly, Quijano and Garrido [47] have shown that when the planning environment is large and the exploration algorithm is not very efficient, the hexagonal representation was shown to perform better than quadrangular grids.

The discretization of the environment was done in a GIS platform (ArcGIS pro version 3.0.3, [48]). Each hexagon represents the properties of the area it covers and these properties are associated with the centroid of the hexagon.

b. Risk determination: Depending upon the sensitivity of the overall mission, stealth can be an important consideration while moving in unfamiliar off-road environments. While planning paths in such environments, one of the cost criteria in the proposed framework is risk, which is modelled as the likelihood of being visible to adversaries. So, a node visible from most of the planning area is the most risky node and vice versa. Carver and Washtell [43] proposed a voxel-based algorithm, which can perform view shed estimation rapidly without significant loss of accuracy [43]. We used their algorithm packaged in MATLAB's "viewshed" function [44] for risk determination. Risk estimation was done in two steps: (1) determining the risk of visibility across the map, and (2) determining the visibility from enemy locations. In the first step, the nodes of the hexagonal grid are used as the observer locations. Using the coordinates of the nodes and the Digital Elevation Model (DEM) of the environment, visibility across the environment from all the nodes are determined and aggregated for each cell of the DEM. The most exposed cell will have the highest value and the least exposed cell will have the lowest value. The aggregated values are then normalized to get a range of visibility risk values between '0' and '1' for each cell. For the second step, the known location of the enemy is used as the observer location and the enemy viewshed is determined, which indicates the areas to be avoided during the path planning stage.

c. Planning data generation: The cost criteria used for path planning are distance, soil trafficability, and risk. The primary concerns when moving in an unfamiliar off-road environment are speed, safety, and stealth [30]. Therefore, distance is used as a cost criteria to ensure shortest paths, soil trafficability is used to ensure safe and traversable areas along the path, and risk is used to ensure minimum exposure when moving along the path (stealth is a future research direction at this time). To estimate the cost criteria values, elevation, soil trafficability, and risk are used as information layers. Soil trafficability is the capacity of soils to support military vehicles [40]. It is determined based on the soil strength, stickiness, slope, slipperiness, and effects of weather [40]. Based on the trafficability ratings, military vehicles are classified into seven classes. Soil trafficability for a vehicle class is a qualitative representation of the soil's ability to allow vehicles of that class to pass over it. These ratings vary based on season (wet or dry) and number of passes. The "Planning and Design of Roads, Airfields, and Heliports in the Theater of Operations–Road Design" [40], jointly published by the U.S Army and U.S. Air Force, provides a scale to convert the qualitative trafficability ratings to a quantitative scale indicating the probability of traversing the area (Table 2). The middle values of the probability ranges were chosen for each qualitative rating. Soil trafficability ratings were obtained from the web soil survey database maintained by the USDA National Resources Conservation Service [45].

Table 2: Soil trafficability ratings and corresponding probability of traversing the area. [40]

Soil trafficability rating	**Probability of traversing the area**
Excellent	90% - 100%
Good	75% - 90%
Fair	50% - 75%
Poor	0% - 50%

The elevation and risk information are imported to GIS in the form of rasters, whereas soil trafficability and obstacle information are imported in the form of vector polygons. The elevation of a node in the hexagonal grid is the elevation at the centroid of the respective hexagon. Similarly, the risk of visibility is also averaged across the hexagon and assigned to the respective centroid. Centroids of all the hexagons that are over the obstacles are classified as obstacles. The hexagons visible from the enemy location are treated as obstacles to be avoided. The planning is done for a point object, so to account for that, centroids (nodes) in the grid which are at a distance equal to the vehicle length from obstacles are also classified as obstacles. Soil trafficability values are averaged for the area covered by a hexagon and assigned to the respective node.

After the planning criteria are assigned to each node of the hexagonal grid, the attribute table of the loaded hexagonal grid is extracted and used for the multi-criteria, multi-agent path planning.

4.2. Multi-Criteria Multi-Agent Path Planning

In this stage, the planning data generated in the preprocessing stage is used to plan paths for multiple agents. The subtasks in this stage are multi-criteria weighting and multi-agent path planning.

a. Multi-criteria weighting: Graph-based planners generate paths for point objects by optimizing the distance between start and the target nodes, but those paths have to actually be traversable by a vehicle for them to be usable. The traversability of a path depends upon the terrain it moves along, the vehicle moving along that path, the soil properties across the environment, etc. The proposed framework considers the soil trafficability and risk information. It also uses terrain properties like longitudinal and lateral slopes to rule out neighbors located at infeasible slopes. The environment properties (risk and soil trafficability) and distance are incorporated into a multi-criteria cost function of the planning framework. The different criteria are normalized and weighted using the entropy weighting method.

Entropy weighting is an objective weighting method, which assigns weights based on the uncertainty represented by a discrete probability distribution of the cost criteria [41]. It weights a criteria more if it is more important in the decision making process, i.e., its values are distributed more across different neighboring nodes [34]. Using this approach produces a different set of weights for each step of the search, which ensures that at each step the more critical criteria is weighted more.

If there are m neighbors and $\mid a \mid$ cost function attributes, the probabilities for the attributes (Y_{ij}) are [34]:

$$Y_{ij} = \frac{X_{ij}}{\Sigma_{i=1}^{m} X_{ij}}, j\epsilon[1, |a|] \quad (2)$$

The entropy value for cost function attribute j (e_j) is calculated as [42]:

$$e_j = -\frac{1}{ln(m)} \Sigma_{i=1}^{m} Y_{ij} * ln(Y_{ij}), j\epsilon[1, |a|] \quad (3)$$

And the corresponding weights are determined as [42]:

$$w_j = \frac{1 - e_j}{\Sigma_{j=1}^{|a|}(1 - e_j)}, j\epsilon[1, |a|] \quad (4)$$

b. Multi-agent path planning: The proposed framework plans multiple paths across the environment, that are conditionally disjoint using a penalty-based A* algorithm [2],[24]. The penalty-based A* algorithm uses the planning data generated in the preprocessing step as the environment data and the planning criteria data. The first path is generated using the A* star algorithm [2] with a multi-criteria cost function. All the nodes present in any previous path are penalized during the search of the next path, and a penalty value is added to the multi-criteria cost function of the penalized node and its neighbors. This further diverges the search and generates paths that are distinct from the previously generated paths. This process is repeated until the desired number of paths is generated.

The cost criteria (distance, risk, and soil trafficability) are normalized and used in a weighted multi-criteria cost function. The normalized value (X_a^{ij}) of a parameter (Z_a^{ij}) for cost attribute a is determined as:

$$X_a^{ij} = \frac{Z_a^{ij} - Z_{a,min}}{Z_{a,max} - Z_{a,min}} \quad (5)$$

Where $Z_{a,min}$ and $Z_{a,max}$ are the minimum and maximum feasible values of the cost parameter *a*.

The heuristic aspect of the cost to be used alongside the multi-criteria cost should underestimate the cost to reach the target node (*t*) [2]. Therefore, for each successor, the heuristic value is calculated to be the ratio of 'the distance between the node and the target' to 'the sum of the distance between all available successors and the target'.

$$h_j = \frac{Distance(j,t)}{\Sigma_j Distance(j,t)} \quad (6)$$

The normalized cost parameters, for each neighboring node, are then supplied with appropriate weights (w_a) to determine the weighted cost of moving from current node *i* to a neighbor node *j*. The multi-attribute weighted cost (c_{ij}) of traveling from node *i* to node *j* is determined as:

$$c_{ij} = \Sigma_a (w_a * X_a^{ij}) \quad (7)$$

$$g_j = g_i + c_{ij} \quad (8)$$

$$f_j = g_j + h_j + q \quad (9)$$

Whereg_i and g_j are the weighted costs to travel from start node (*s*) to nodes *i* and *j*, respectively. The f-cost (f_j) of node *j* is the sum of g-cost (g_j) and h-cost (h_j) for node *j* and a penalty *q*. The penalty is 0 if a neighboring node was not used in a previous path or is not an immediate neighbor of a node used in a previously planned path.

5. RESULTS AND DISCUSSION

The proposed multi-criteria, multi-agent path planning framework was implemented on a terrain map. An off-road environment near Elmore County, Idaho was chosen. The test terrain had no formal road network. It had elevation variations, soil trafficability variations, and obstacles in the form of water bodies. The selected test area was about 46,000 sq meters, of which a Digital Elevation Model was obtained from the U.S. Geological Survey's website [49]. An arbitrary location on the map was chosen as the enemy location, shown by a blue pin in Figures 2 through 11. The study area was discretized into a hexagonal grid (Fig 1) with each hexagon of 5000 sq meters area. This yielded a centroid distance of 75.98 meters between adjacent hexagons. The information layers for the environment are shown in Fig. 2 through Fig. 6 (underlying map source is [50]).

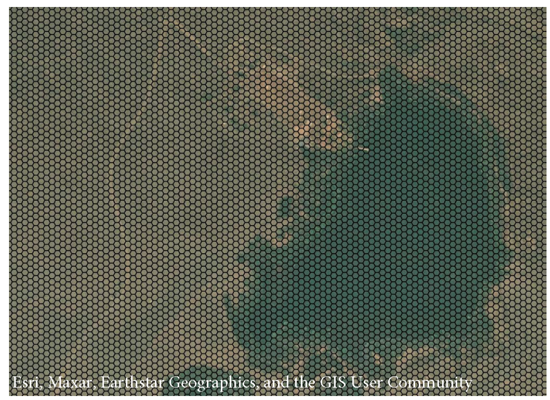

Figure 1: Hexagonal grid representation (zoomed in).

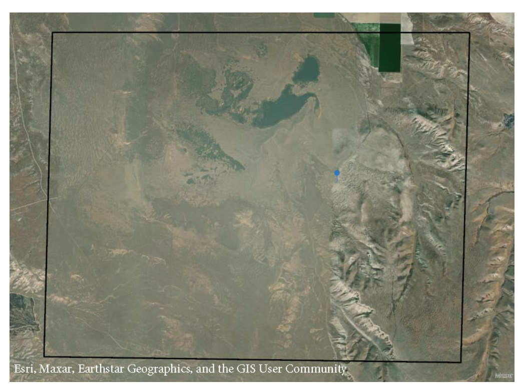

Figure 2: Test terrain extent.

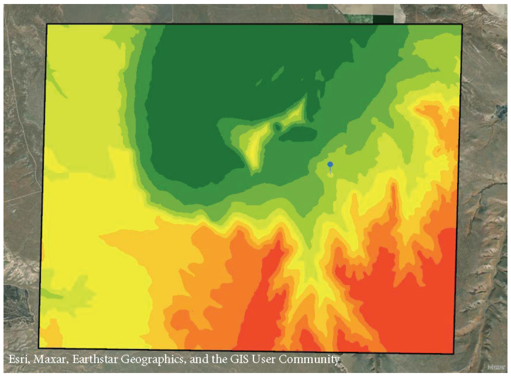

Figure 3: Elevation layer.

Due to the nature of the environment and the grid, distance was mostly uniform across neighboring hexagons. There was variation in soil trafficability, but risk had the most variation of the three cost parameters, across neighboring hexagons. These characteristics could result in long winding paths, which mostly optimized risk and soil trafficability. To ensure distance is also optimized along with soil trafficability and risk, a value of 1 (subjective bias) was added to the weights generated by the entropy method for the distance criteria.

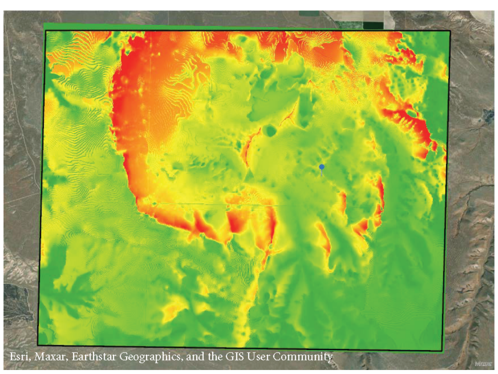

Figure 4: Risk Layer.

The penalty value should be chosen such that the search diverges from the original set of nodes. Thus, a factor of the estimate of the cost between any two neighboring hexagons is representative of the penalty. For this test, a penalty of 6 was chosen, any node present in a previously planned path was penalized. On top of that, immediate neighbors of a penalized node were also penalized to cause further distinction of the paths.

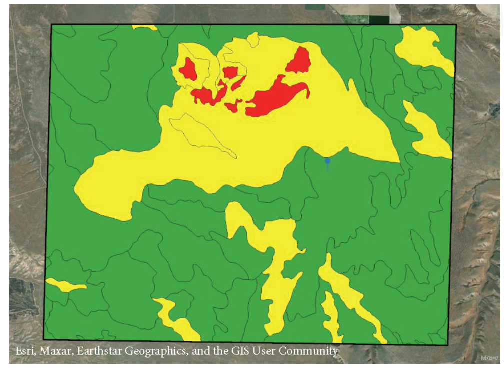

Figure 5: Soil trafficability layer.

The resulting paths are shown in Figures 7 through 11. The magenta path is the first path and the blue path is the second, generated using the penalty mechanism. The total path length, average risk per node, and average soil trafficability per node are compared for the two paths generated by the multi-criteria, multi-agent path planner (MCMAPP), against the paths generated by optimizing each of the cost criteria and the plots are shown in Figures 12 through 14.

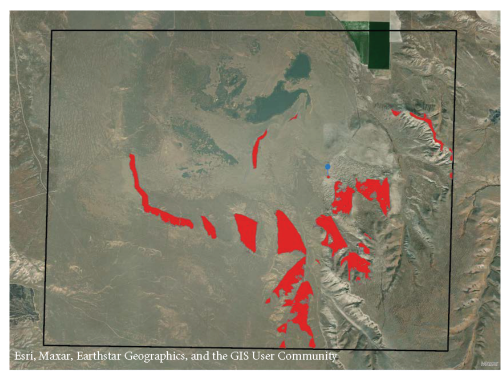

Figure 6: Enemy viewshed.

The paths generated by MCMAPP perform better than all other planning strategies except the optimal one, for soil trafficability and for risk. The path length for the first MCMAPP path is the highest of all the paths generated. For the second MCMAPP path, the length is close to the optimal path length. The risk per node for the first path planned by the MCMAPP is lowest, lower than the risk per node for the optimal risk planning strategy. This is because the optimal risk planning strategy minimizes the cumulative risk along the path. The cumulative risk is therefore lowest for the optimal risk planning strategy, but the first MCMAPP path does better when it comes to *average exposure to risk* along the path. As for the average soil trafficability, the MCMAPP paths have high average soil trafficabilities per nodes, and are only bested by the optimal soil trafficability path.

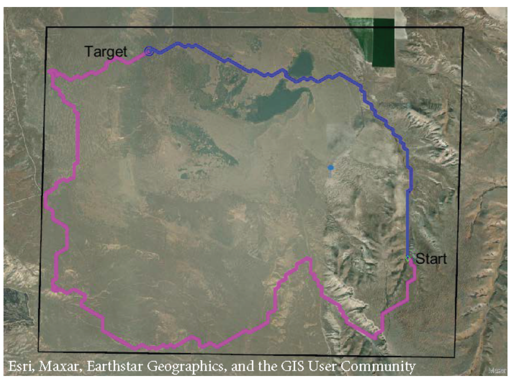

Figure 7: Results on test terrain extent.

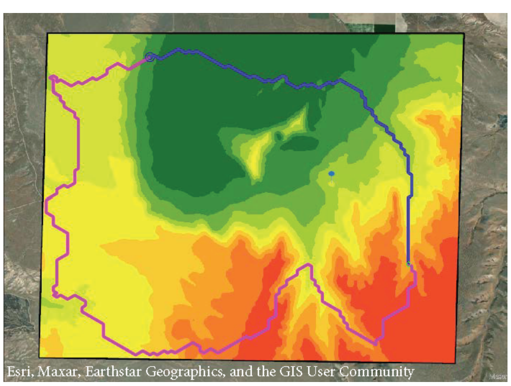

Figure 8: Results on elevation layer.

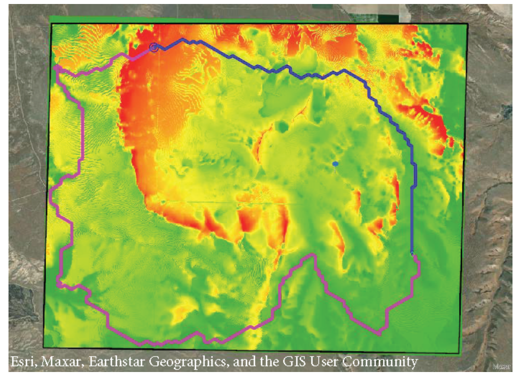

Figure 9: Results on risk Layer.

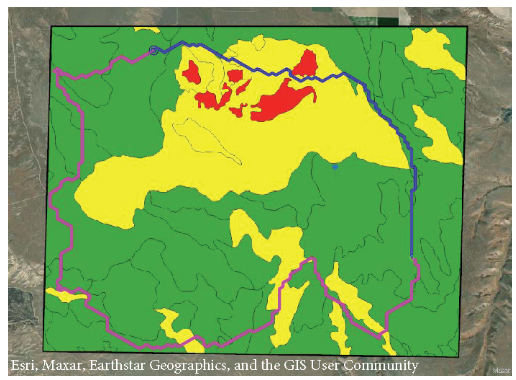

Figure 10: Results on soil trafficability layer.

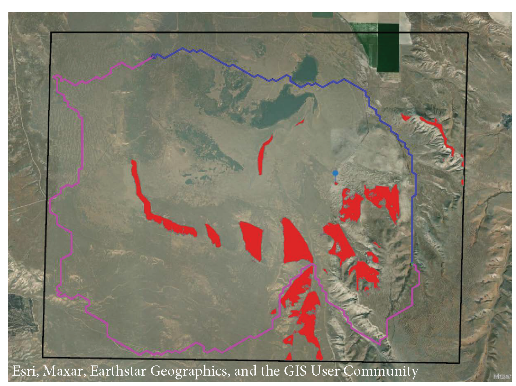

Figure 11: Results with enemy viewshed.

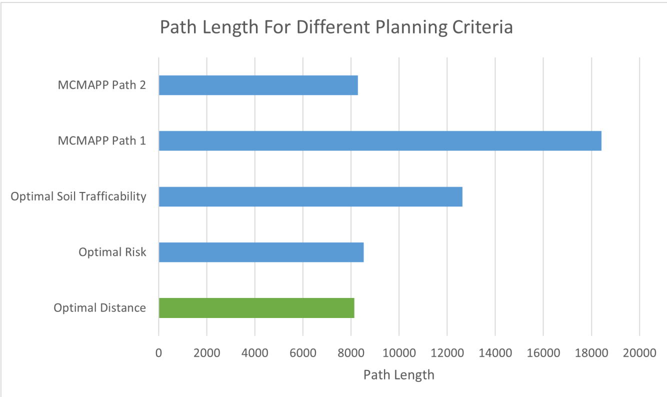

Figure 12: Comparing path length.

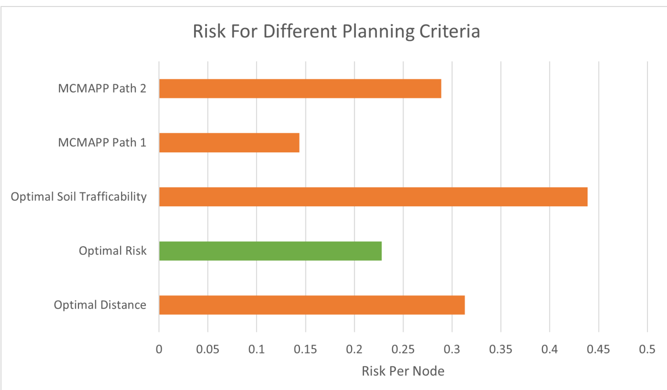

Figure 13: Comparing average risk per node.

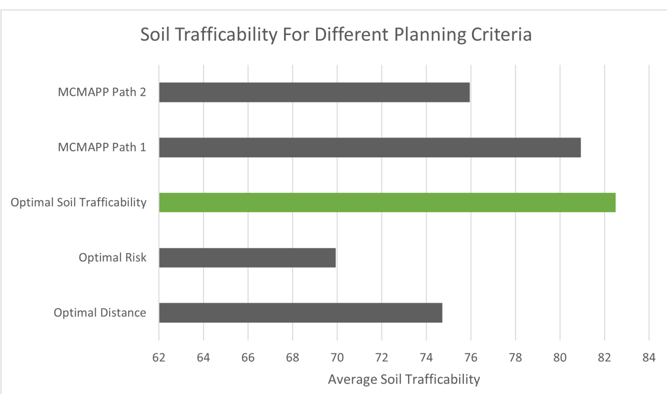

Figure 14: Comparing average soil trafficability.

6. CONCLUSION AND FUTURE DIRECTIONS

The proposed framework plans paths for multiple UGVs traversing in unstructured off-road environments. It incorporates the environment properties to ensure safe paths. Such a framework can help in routing unmanned vehicles in off-road environments for humanitarian relief after natural disasters, transporting supplies to off-road locations, etc. Using UGVs for these missions can decrease the risk to human drivers that are otherwise involved in such missions. It can also supplement a low-level local planner by providing a set of waypoints to help keep a UGV on track towards the target. A significant limitation of our framework is that the run time significantly increases as the environment becomes larger. However, this framework is meant to be run before the mission to provide waypoints before the UGVs leave their starting location. The second limitation is that the proposed framework does not consider vehicle properties, yet.

A penalty is being used to generate multiple paths, this introduces an additional parameter that needs to be tuned to generate desirable paths. Using this approach comes with its pros and cons. The advantage being, the value of penalty and the penalty assignment mechanism can be tuned to generate paths that are desirable to the operator. However, a disadvantage is the fact that the operator needs to have some information about the multi-criteria cost to generate good estimates of the penalty.

The proposed MCMAPP assumes that the input environment information is perfect, and plans paths based on that information. However, in reality the *a priori* data may not reflect the changes that may have occured in the real environment. This limitation, however, could be addressed by replanning as needed. Imperfect information could also be addressed by adding another attribute such as "information reliability" or a "trust value" to the routing considerations. The proper way to integrate this attribute with the other elements requires additional research into whether it is an independent attribute or needs to be combined with the other data elements (e.g., multiplicatively).

Incorporating vehicle properties in the

multi-criteria path planning framework is the next step for this research. In addition, using travel time as a cost criterion instead of distance could potentially eliminate the need to add subjective bias to the weights. Furthermore, this work can be expanded by implementing a fast-replanning capability, so that the original plan can be updated to accommodate any discrepancy in the environment identified during the mission or for situations when the vehicle significantly deviates from the original plan.

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