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ROUTE PLANNING FOR AUTONOMOUS UNMANNED GROUND VEHICLE OPERATIONS IN URBAN ENVIRONMENTS

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ABSTRACT

Route planning plays an integral role in mission planning for ground vehicle operations in urban areas. Determining the optimum path through an urban area is a well understood problem for traditional ground vehicles; however, in the case of autonomous unmanned ground vehicles (UGVs), additional factors must be considered. For a UGV, perception, rather than mobility, will be the limiting factor in determining operational areas. Current ground vehicle route planning techniques do not take perception concerns into account, and these techniques are not suited for route planning for UGVs. For this study, perception was incorporated into the route planning process by including expected sensor accuracy for GPS, LIDAR, and inertial sensors into the path planning algorithm. The path planner also accounts for additional factors related to UGV performance capabilities that affect autonomous navigation.

INTRODUCTION

In general, route planning for ground vehicles through a known area of interest involves finding the shortest path between two points that contains no obstacles [1]. Several methods have been developed to find the optimal path between two points, the most popular of which remains the A* algorithm first developed by Hart, Nilsson, and Rapheal in 1968 [2] and its multiple variants found in [3]. Trafficability obstacles can be defined in many ways depending on the capabilities of the ground vehicles in question, i.e., sharp turns, steep slopes, rough terrain, etc, and for manned ground vehicles the problem of path planning is considered solved.

However, these path planning algorithms do not provide a complete solution for the case of autonomous unmanned ground vehicles (UGVs). Additional factors affect autonomous navigation beyond those that affect traditional ground vehicle mobility, and the best route for an autonomous UGV is not necessarily the shortest path. The limiting factor for autonomous operations will most likely be perception, not platform mobility. The UGV's ability to accurately sense its environment determines its ability to successfully navigate a path; therefore, an ideal path planning algorithm for UGVs should take into account the accuracy of the sensor outputs used to drive autonomy algorithms.

Furthermore, what constitutes an obstacle for an autonomous ground vehicle is not clearly defined. Most autonomy systems have some built-in fault tolerance and performance limitations that cannot be fully captured using binary go-nogo obstacle definitions. For example, when defining obstacles for a UGV that can handle some GPS drop-out, quantifying 'some' GPS drop out is a difficult task. Or in the case of an autonomous navigation system that can handle 'moderately sharp' but not 'very sharp' turns. A successful path planner for autonomous UGVs must take into account the performance capabilities and limitations inherent in autonomy systems.

This paper presents the development and implementation of a new path planning algorithm for autonomous UGV operations in urban environments. Average sensor error values for the most common sensors used for autonomous navigation, i.e., a laser range finder, an inertial measurement unit, and a GPS receiver, were calculated using high-fidelity sensor simulations. Details on the sensor errors, their calculation, and the simulation environment used can be found in the Experiment section. The error values at each point within the urban area were fused into a single map grid cell, or node, cost. Likewise, to handle qualitative inputs related to autonomy algorithm performance limitations, fuzzy set theory was used to create a set of rules to further refine the route planning process. The resulting path planning algorithm and its application for UGV route planning is presented in Route Planning Section. Lastly, the Conclusions section provides some conclusions and recommendations for future efforts.

EXPERIMENT

High-Fidelity Sensor Simulations

The data for this study were generated using the Virtual Autonomous Navigation Environment (VANE) computational testbed (CTB), a high-fidelity, physics-based simulation environment for the design, development, and evaluation of autonomous UGVs developed by the US Army Engineer Research and Development Center (ERDC). By leveraging advances in High Performance Computing (HPC) tools, VANE can be run in a practical time frame, with simulations running 5 to 15 times slower than real time. Using ERDCs Cray XE6, VANE performs parallel computations of radiative transfer for simulations of GPS and LIDAR sensors. VANE also uses complex vehicle-terrain interaction models to produce highly realistic inertial measurement unit (IMU) sensor simulations. These high-fidelity sensor simulations are then used to simulate the outputs for sensor packages commonly found on robotics vehicles.

An in-depth review of the VANE CTB is beyond the scope of this paper; a full description of the VANE CTB can be found in [4] and [5]. In particular, this study leveraged the physics-based sensor models contained within the VANE CTB, which are described in detail in [6]. For this study, LIDAR, GPS, and IMU sensor data were generated along the road network of a typical urban environment.

Simulation Scene

Figures 1 and 2 show the urban environment that was used as the simulation scene. The scene chosen was a typical urban cityscape roughly two km by two km and containing approximately 1700 buildings. The scene was chosen because it contains many features known to challenge autonomous navigation systems. These features include urban canyons (narrow roadways surrounded by tall buildings which result in significant GPS dropout), tight turns, narrow and constricted roads, and barriers made of razor wire, which is especially difficult for LIDAR to detect.

The urban scene must first be translated into a go-nogo matrix to be input into the path planning algorithm. This was accomplished by first down-sampling the urban height map to generate a six-meter resolution digital elevation map (DEM). Then, each cell that was occupied by an object (building, street lamp, etc.) was assigned a node value of -1. This process created the base set on which the standard A* path planning algorithm would operate, wherein every node with a value of -1 was taken to be an obstacle. When applied to this input set, the A* algorithm returns simply the path which minimizes distance. The base road network for the scene is show in Figure 3.

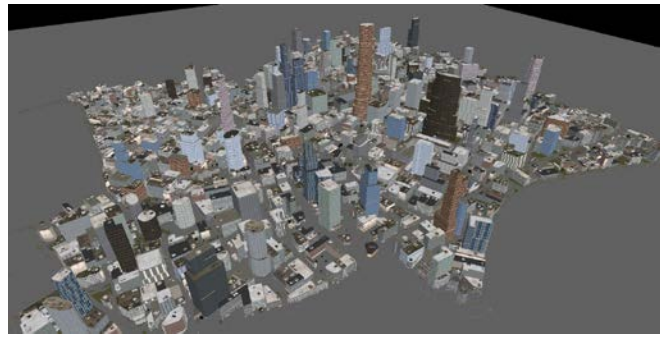

Figure 1. The urban scene.

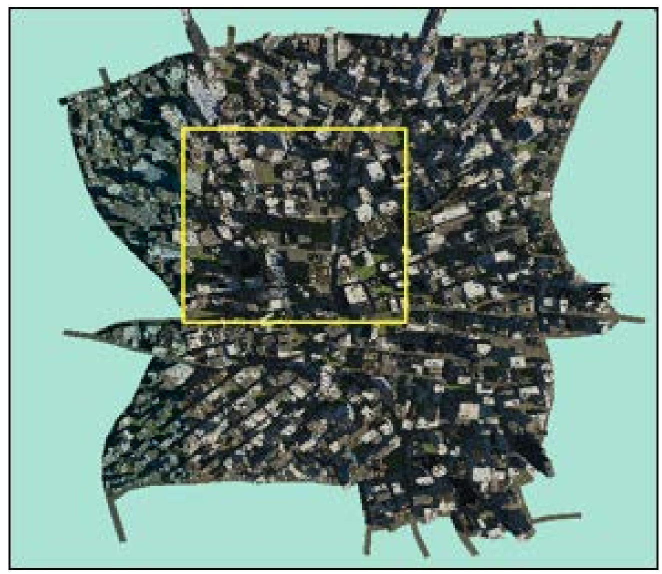

Figure 2. An overhead view of the scene. The yellow box contains the area of interest selected for route planning.

Simulating Sensor Errors

The GPS position was simulated along the six-meter road network grid at a height of three meters above the ground. To generate the average GPS error values, the GPS was simulated collecting stationary position data at each node for two hours. The output receiver position was compared to the true receiver position within the scene, and the average GPS error for each grid cell was determined using the equation below.

$$GPS_{err}(x,y) = \frac{1}{N}\sum_{i=1}^{N} GPS_{sim}(x,y,t_i) - (x_{true}, y_{true})$$

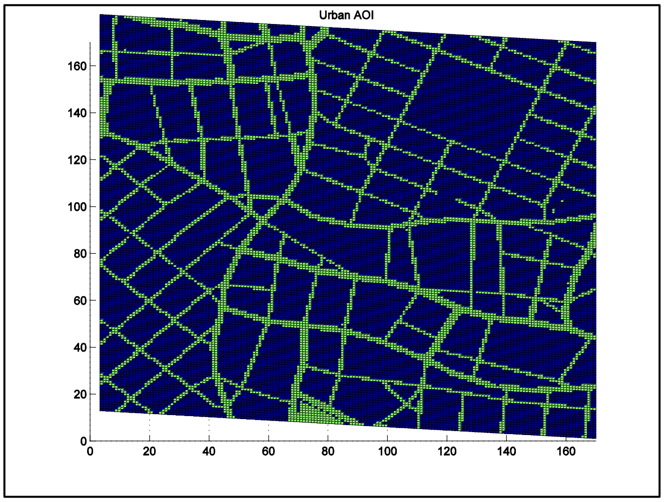

Figure 3. The road network contained within the yellow box in Figure 2.

Note that the GPS error does not take into account errors in the z-direction. This exclusion is due to the large errors inherent within GPS altitude measurements, and GPS altitude measurements are rarely used by autonomous navigation systems. Once calculated, the GPS errors were normalized to have maximum value of one in the case of GPS dropout and scaled values of 0.99 to 0.01 for grid cells with GPS returns. Figure 4 shows the GPS errors along the road network.

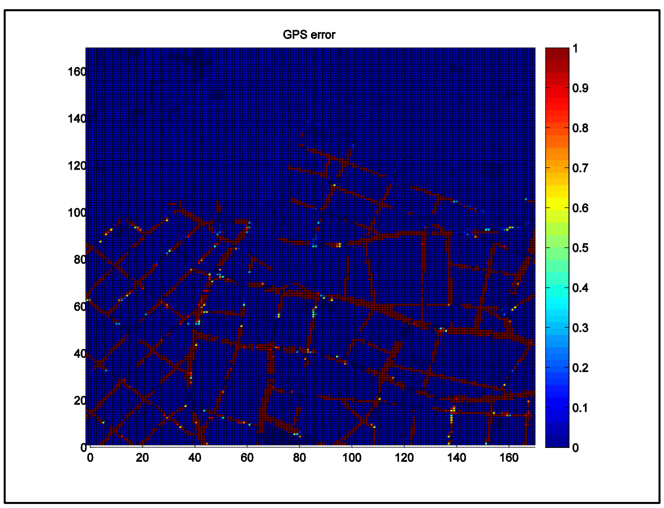

Figure 4. The predicted GPS error along the road network.

The LIDAR sensor error was generated using a method similar to that of the GPS sensor. For each node along the road network, one LIDAR scan was performed using a 3D LIDAR sensor. The simulated point cloud was then compared to the point cloud generated using an 'ideal' LIDAR, i.e., one that does not suffer from beam divergence and reflects perfectly from all surfaces. The average error at each grid cell was computed in the same fashion as the GPS error, as can be seen in the equation below. Figure 5 shows the LIDAR errors along the road network, which have been normalized to a maximum value of one.

$$LIDAR_{err}(x, y, z) = \frac{1}{N}\sum_{i=1}^{N}\sqrt{(x_{sim} - x_{ideal})_i^2 + (y_{sim} - y_{ideal})_i^2 + (z_{sim} - z_{ideal})_i^2}$$

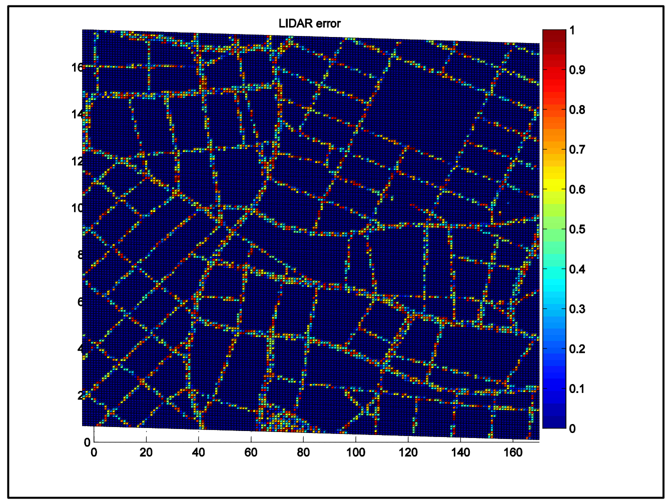

Figure 5. The predicted LIDAR error along the road network.

Because of the physical performance limitations of the accelerometers used in these systems, all IMU sensors suffer from drift, scale, and bias effects. Therefore, the greater the distance traveled or the longer the time of operation, the more the IMU position estimate will degenerate. Given that most commercial IMU units will be calibrated to compensate for scale and bias, the IMU error was estimated as the drift in the sensor multiplied by the total distance traveled, and the error values where then normalized. Figure 6 shows the IMU errors along the road network, with the assumption that the sensor is traveling at a constant speed starting at the bottom right corner of the map and moving towards the top left corner.

ROUTE PLANNING

For manned ground vehicles, path planning can be fully realized using nodes that are either closed (contain obstacles) or open, and the A* algorithm is used to find the shortest open path between the start and goal points. Therefore, the natural starting point for the development of a new route planning methodology is the application of A* to the urban road network shown in Figure 2 to determine the base case. Figure 7 shows the optimal path determined by A* in the absence of sensor errors. The path was chosen to have a start point of (12, 5) and a goal point of (157, 157). It has a total distance traveled of 213 nodes and a total path cost as defined in [1] of 256.08. These cost and distance values serve as the ’best case’ values, and subsequent paths planned will require some tradeoff between cost, distance traveled, and avoidance of sensor errors.

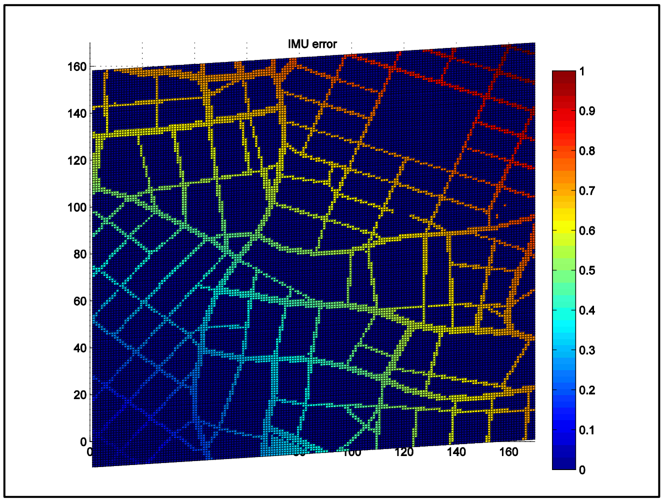

Figure 6. The predicted IMU sensor error along the road network.

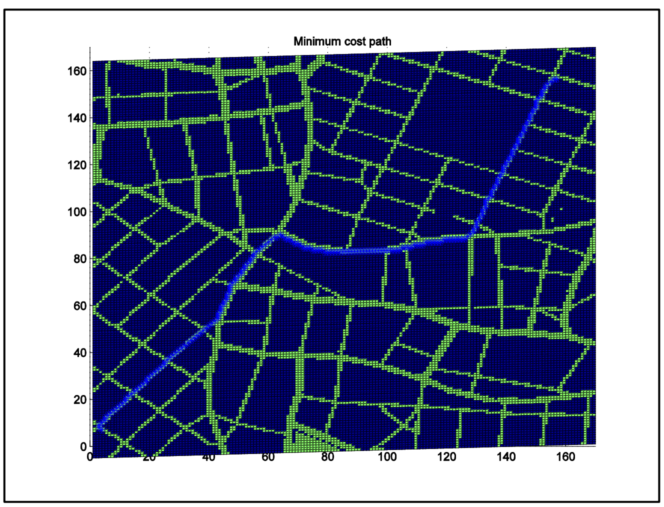

Figure 7. The shortest route between the start and goal points.

The simplest way to incorporate sensor accuracy into the path planner is to add the total sensor error values at each node along the road network and make the cost of traveling to each node the total sensor errors. In this case, A* will return the path with the lowest total cumulative sensor error while also attempting to follow the shortest path; therefore, the path returned is the shortest path that minimizes sensor

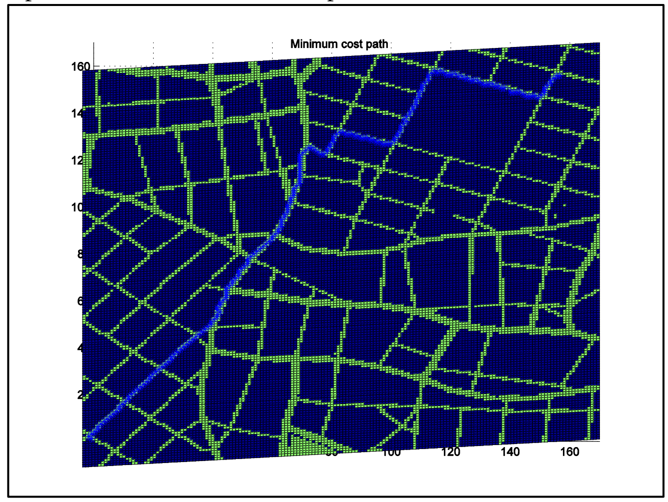

Figure 8. The route with minimum cumulative sensor errors.

error, and not necessarily the path with the absolute minimum total cumulative error. The route planned between the start and goal points in this case is shown in Figure 8. From a mobility standpoint, this is a less optimum path, having a total distance traveled of 226 grid cells and a total path cost of 306.48. Furthermore, this path can be qualitatively described as having many sharp turns, a switchback, and following several narrow roadways.

The specific means of combining the sensor errors into a node cost is highly dependent on the UGV platform and autonomy algorithms, and different combinations will be better suited for different situations. A more interesting and ultimately more useful tool is a set of rules for further refining what an ’optimal’ path is. Using some techniques from fuzzy set theory [7], a few simple rules can be defined and applied to the route planning algorithm.

For example, many autonomous UGVs make use of a combination of GPS and IMU data for localization. As such, the system can handle large GPS errors as long as the IMU errors remain low. Figure 9 shows the route planned in case of following a route with low GPS error unless IMU error is low. The path skirts around the large area of GPS drop-out near the starting point, and this path is much better for the case of an autonomy system that requires a high-fidelity localization. Similarly, many autonomy algorithms require highly accurate LIDAR and positioning data, and these systems cannot tolerate high errors in both LIDAR and positioning data. Figure 10 shows the road network with node costs for a UGV that requires either highly accurate LIDAR or highly accurate positioning data at each node. As

Figure 10 shows, a UGV with this limitation could not navigate between the start and goal points (no open path exists between the start and goal points).

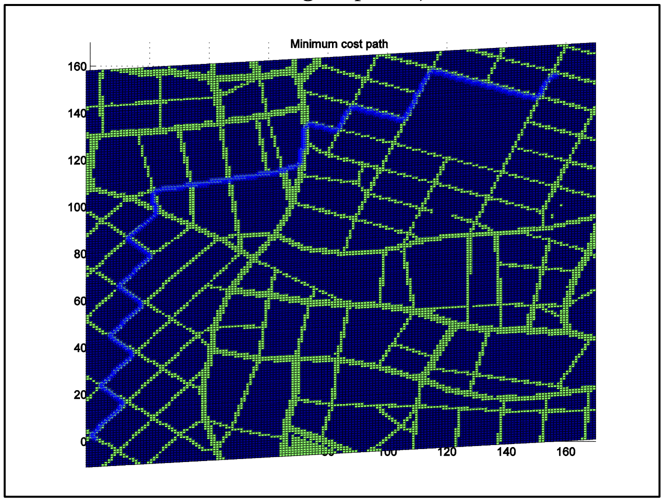

Figure 9. The route chosen when allowing for high GPS error when IMU error is low. This route successfully avoids the large area of GPS dropout near the bottom right corner of the AOI.

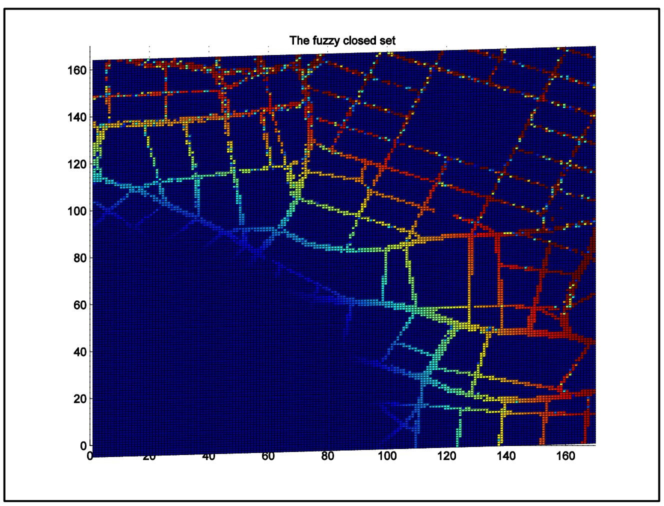

Figure 10. The road network with node costs for a UGV that requires either highly accurate LIDAR or highly accurate IMU/GPS data. Red nodes have a cost of -1 and are closed, and no route exists between the start and goal points in this case.

One interesting application of the fuzzy route planner is that it can be retrospectively applied to a path. That is, for a given path through the scene, what errors where present and what rules where followed in the generation of that path? Performance evaluation for autonomous UGVs is an active research area with many outstanding problems, and this could provide some insight into how a UGV's performance could be assessed. Given that a UGV navigated autonomously through an area, and provided with the UGV's chosen path, it is possible to measure how 'good' of a path the autonomous navigation algorithm chose and what factors most impacted the UGV's choice of path.

For example, Figure 11 shows the path of least distance between the nodes (140, 3) and (3, 151). The path has a total distance of 203 nodes with 103 nodes containing GPS dropout, so this path is clearly not optimized for a UGV that is dependent on GPS data. However, a UGV that traveled this path can be said to be capable of handling prolonged periods of GPS denial.

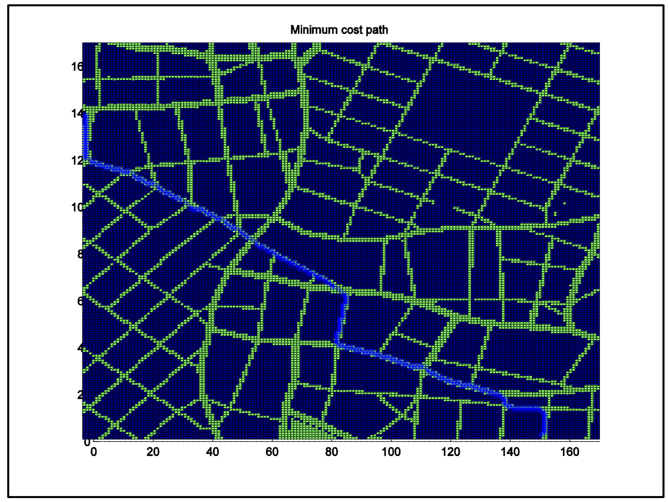

Figure 11. A random path through the AOI. By applying the route planner retrospectively, this path is shown to be sub-optimal for a UGV dependant on GPS data.

CONCLUSIONS

In many cases, traditional methods of route planning and performance prediction for ground vehicle operations prove insufficient for autonomous UGVs. The current mission planning and performance assessment tools prove inextensible to autonomous systems, and new methods must be developed. One such area in which traditional methods are not well suited to autonomous operations is route planning through urban areas. For traditional ground vehicles, paths can be planned using well understood mobility concerns and obstacle definitions. On the other hand, for autonomous navigation, the impact of sensor outputs and autonomy capabilities must be taken into account. With that in mind, a route planning algorithm for autonomous navigation through urban environments was developed.

The new path planner took into account predicted accuracy and expected errors in sensor outputs for the sensors most commonly used for autonomous navigation: GPS, LIDAR, and IMU sensors. The relative accuracy of the sensor outputs at each node affected the cost associated with traveling to that node, and the path planner searched for the shortest path that also minimized the cumulative errors for those sensors critical to autonomous navigation. Additionally, some fuzzy, qualitative rules where applied to the path planner which allowed the algorithm to adjust for the performance characteristics of different UGV systems. In this way the path planner was able to optimize paths for UGVs using qualitative information about the UGV's inherent capabilities, an ability that previous path planning algorithms lacked.

In addition, the path planner can be run 'in reverse' to analyze the paths chosen by an autonomy system to glean some characteristics about the autonomy system's performance. Paths could be analyzed to determine what sensor errors where minimized by the autonomy system and what rules the autonomy system tried to follow. This analysis could serve as a metric for measuring a particular UGV system's path planning performance through an area, for evaluating its capability to avoid areas of high sensor error and/or to follow a more direct route, and for other such questions.

This study represents only a first-look case for extending route planning methodologies to path planning for autonomous ground vehicles. It provides a framework which is easily extensible for many different UGV systems with a range of sensors and autonomy algorithms. Going forward, many more rules should be developed and implemented and additional sensors, such as cameras, should be included into the path planner. The early results presented in this study are promising, and show that further development of a more robust and fully realized path planning algorithm would have a positive impact on the ability to field autonomous assets and predict their performance.

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