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A REFERENCE AUTONOMOUS MOBILITY MODEL

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ABSTRACT

Mobility modeling is a critical aspect of the ground vehicle acquisition process. Mobility modeling for traditional ground vehicles is well-understood; however, mobility modeling tools for evaluating autonomous mobility are sparse. Users do not understand the performance capabilities of autonomous ground vehicles at a mission level because no mission-level mobility model exists for autonomous vehicles. Therefore, this paper proposes a Reference Autonomous Mobility Model (RAMM). The RAMM serves as the mission-level mobility modeling tool that is currently lacking in the unmanned ground vehicle (UGV) community. The RAMM is built on the framework already established by trusted mobility modeling tools to fill the current analysis gap in the autonomous vehicle acquisition cycle. This paper gives a detailed description of the RAMM along with an example application of the RAMM for modeling autonomous mobility. Once fully developed, the RAMM could serve as an integral part in the development, testing and evaluation, and fielding of autonomous UGVs.

1 INTRODUCTION

Unmanned Ground Vehicles (UGVs) are an emergent technology that is reshaping operations for private, commercial, and military ground vehicle applications. From the Google car (Poczter and Jankovic 2014) to autonomous military resupply convoys (Zimpfer, Kachmar, and Tuohy 2005), UGVs are being fielded in increasing numbers for an increasing number of missions. In particular, increased autonomy and robust autonomy algorithms are a key factor in current UGV research, and autonomous UGVs are beginning to be tested in the field. As UGVs become more autonomous, the key performance measures that define a ground vehicle's performance capabilities will need to be modified and redefined. One such performance measure that affects UGV operational performance is platform mobility.

For ground vehicles, mobility is a well-understood problem, and many of the performance measures that define mobility are set. For example, driver response time and willingness to endure rough terrain can readily be integrated into a mobility model. While the base mechanical mobility platform is, for the most part, the same between manned and unmanned ground vehicles, there are stark differences in their total overall mobility. For example, autonomy algorithm response time and durability of sensor systems when traversing rough terrain are not fully understood. For manned ground vehicles, mobility is based on mechanical and driver-centric factors. However, for an autonomous UGV, driver-centric factors must be replaced with sensor and perception-centric factors. For example, visible sight distance for a human is different from that of a camera or LIDAR, meaning sensor range should be used to determine mobility. This difference is only one example of how autonomy changes mobility; in general, the factors that affect autonomous mobility are not yet well defined.

Using defined performance parameters, analysis tools for measuring ground vehicle performance capabilities at an operational level have been developed. One of the more frequently used of these tools is the NATO Reference Mobility Model (NRMM), which is discussed briefly in Section 2. The NRMM was first developed in the 1970s and is still used in the military ground vehicle acquisition process today. This type of performance assessment tool can be used across the vehicle acquisition cycle, from development to testing and evaluation to fielding. It provides a snapshot of how the vehicle will operate during its mission, where it can and cannot travel within a given terrain, and the impact of design changes on the vehicle's mission performance capabilities.

A mobility modeling tool for autonomous UGVs that provides detailed information on a UGV's autonomous performance for a given mission on a given terrain would help accelerate the use of autonomy for military applications. By providing users with a robust understanding of the impact autonomy has on mission-level performance and the performance capabilities of an autonomous UGV, users would have more confidence in employing autonomous UGVs for a wider range of missions. Given the need for such a performance assessment tool, this paper proposes a tool for modeling autonomous mobility; the Reference Autonomous Mobility Model (RAMM).

The goal of this paper is to briefly describe the NRMM and extend the NRMM into the RAMM in a logical fashion. The next section gives a short overview of the NRMM, Section 3 proposes the RAMM, Section 4 provides details on the Virtual Autonomous Navigation Environment (VANE), a simulation tool that serves as the backbone for the RAMM, Section 5 shows an applications of the RAMM and how the RAMM operates, and Section 6 provides some conclusions and closing thoughts.

Throughout this paper, frequent references are made to "autonomy algorithms" and "sensor-centric / sensor-based" mobility modeling. "Autonomy algorithms" refer to any intelligence software used by the UGV for navigation purposes. These algorithms take in sensor data and uses them to reason about the world and decide the course of action for the UGV. The autonomy algorithms are akin to the human driver for traditional ground vehicles. "Sensor-centric / sensor-based" factors refer to the physical limitations of the UGV sensor systems. These factors determine the accuracy and availability of data to feed the autonomy algorithms. So, for autonomous mobility, the sensor-centric factors will determine overall mobility. This idea is fleshed out in full in Section 3.

2 THE NATO REFERENCE MOBILITY MODEL

Recognizing the need for a modeling tool that could answer important questions about the viability of a ground vehicle for a particular mission and environment, the Army developed a mobility modeling tool for off-road vehicle performance (the Army Mobility Model), which was quickly improved upon and adopted by NATO in the 1970s. At its heart, the NRMM is a parameterized model, meaning the ground vehicle and the environment are both simplified into a set of parameters, and the vehicle parameters are compared against the environment parameters using empirical mobility models to determine overall mobility. The NRMM works by comparing the vehicle data to the environment data using empirical relations developed through field testing to determine if the vehicle can cross a particular patch of terrain and, if so, at what speed can it operate. This output is referred to as "speed-made-good." A generalized workflow of NRMM, including its sub-modules, is shown in Figure 1.

The NRMM provides several key abilities to both ground vehicle developers and military decision makers. By varying the vehicle parameters, users are able to quickly weigh the benefits of system design choices and perform module tradeoff studies. Users can also leverage the NRMM as a planning tool to determine what ground vehicle is best for employment in given situations. Because of these features and despite its age, the NRMM is still the primary mobility modeling tool used in the ground vehicle acquisition process. Several important references decribing the NRMM can be found, including (Petrick, Janosi, and Haley 1981) and (Ahlvin and Haley 1992).

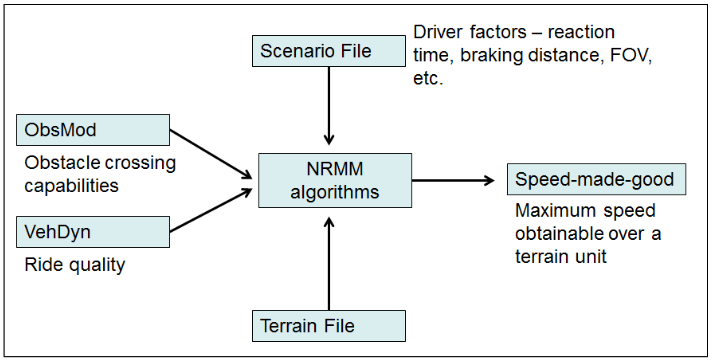

Figure 1: The NRMM workflow.

3 THE VIRTUAL AUTONOMOUS NAVIGATION ENVIRONMENT

The Virtual Autonomous Navigation Environment (VANE) is a high-fidelity, physics-based simulator for autonomous UGVs. The VANE began development primarily as a tool for developing autonomy algorithms for UGVs (Jones 2008) (Cummins 2008). The VANE is used to simulate an autonomous UGV performing a given mission in a given environment. As VANE has developed, it has shifted towards primarily being a tool for simulating sensor-environment interactions with less focus on autonomy in the loop simulations (Goodin, Kala, Carrrillo, and Liu 2009) (Goodin 2010). Where the NRMM is a coarse, macro-scale performance forecasting tool, the VANE is a micro-scale, mission-level simulation tool for performance assessment and algorithm development for autonomous UGVs. As discussed in the following section, the final RAMM formulation relies on the simulation of sensor systems within VANE and the impact these sensor data have on autonomy algorithms.

There are several key components to the VANE. First and foremost is the architecture, which serves as the means by which the other pieces of the VANE communicate with each other. The most important part of the VANE, and the part that will play the biggest role in the RAMM, is the sensor and environment models that are used in the development and testing of autonomy algorithms. On top of the sensor modeling is the mobility and vehicle dynamics models. These models provide the location of the UGV relative to the environment, which in turns provides the location of the UGV's sensors as they perceive the environment. These mobility and sensor models together recreate the physical behaviors of the UGV as it reacts to its autonomy algorithms.

3.1 VANE Architecture

The VANE architecture is modeled after the High-Level Architecture (HLA) concept used in DoD simulations. In this architecture, federates, or models, subscribe to and publish outputs of pre-defined formats. Because the VANE is non-real-time and the VANE's models work at disparate time scales, the advancement of time is controlled by a time-manager federate that tracks the internal state of each of the participating federates (models). In typical VANE simulations, sensor federates subscribe to the vehicle state message and publish sensor data. The autonomy federate subscribes to both the vehicle state and sensor data messages. The autonomy federate publishes driving commands that are used to determine the vehicle state at the next time step. The HLA architecture controls the messages sent back and forth between these pieces to create a complete VANE simulation.

3.2 VANE Sensor and Environment Modeling

The core of the VANE is its sensor and environment models. Sensor outputs drive the autonomy algorithms used by UGVs. By providing high-fidelity, physics-based simulated sensor outputs, the VANE can more accurately simulate autonomous UGVs behaviors. The mechanism by which the VANE generates high-fidelity sensor outputs is its ray tracer.

The VANE ray-tracer (VRT) uses high-performance computing to simulate the radiative transfer of energy through the environment. The VRT is a full spectral simulation that calculates spectral reflectance properties using either the cosine lobe model or the He-Torrance-Sillion-Greenberg (He, Torrance, Sillion, and Greenberg 1991) bidirectional relectance distribution function (BRDF) model for surface reflectance. Subsurface scattering and transmission are not modeled in the VANE. The atmosphere is modeled in VANE using the Hosek-Wilkie Sky model in the visible region (Hosek and Wilkie 2012) and the Bird (Bird and Riordan 1986) model in the near-IR (NIR) to long-wave IR (LWIR) regions of the spectrum.

To obtain high-fidelity sensor outputs, a high-fidelity environment is required. The simulation environment itself must contain physical data to stimulate the sensors. The environment must contain not just the geometry of each object but also critical physical information, such as spectral reflectance. Moreover, the environment will look different to different sensor models. The modeled BRDF is critical to LIDAR and camera models, but not to GPS, which is more concerned with geometry. For the UGV mobility platform, the environment should contain the soil strength of the ground surface. Figure 2 shows an example VANE geo-environment.

Figure 2: An image of part of an example VANE environment of a forest geo-environment. In addition to the geometry of the environment, objects are given physically meaningful attributes that drive the sensor models.

The VANE contains models for the sensors most commonly used by autonomous UGVs, e.ge. camera, LIDAR, and GPS sensors. The camera model includes both near-IR and hyperspectral cameras in addition to traditional charged-coupled device (CCD) digital cameras. The LIDAR model is a general model that uses ray tracing to simulate the individual laser beams as they propagate through the environment. It is parameterized to match the performance of a variety of LIDAR sensors. The GPS model includes both commercial and differential GPS sensors. Figure 3 shows an example simulated sensor output for a CCD camera.

3.3 VANE Mobility and Vehicle Dynamics Modeling

Vehicle dynamics in the VANE are modeled using the Mercury package from the Computational Research and Engineering Acquisition Tools and Environments Ground Vehicles program (Post 2016). Mercury is built on the Chrono dynamics engine (Tasora 2015) and provides a high-fidelity, physics-based software tool for conducting simulations of vehicle mobility. By integrating cutting edge, massively parallel modeling techniques for soft, cohesive soil and dry granular soil that integrating state-of-the-art soil simulation with

Figure 3: An output image from a Sony CCD camera compared with the real object being modeled within the geo-environment.

high-fidelity multi-body dynamics and powertrain modeling, Mercury provides a next-generation mobility simulation.

3.4 VANE Sensor Accuracy Simulations

Outside of closed-loop simulations, the VANE sensor models can also be used "off-line" to generate sensor data within an environment. In particular, sensor data quality, or accuracy, can be measured within the environment. Because the ground-truth geometry and positions are known, sensor outputs can be compared to these truth data to measure the sensor data error at that position within the environment. Figure 4 gives an example of this sensor accuracy measurement for a GPS sensor. This GPS sensor study is revisited later in this paper as an example application of the RAMM.

These sensor accuracy prediction maps in particular mimic the NRMM. They provide an environment in which mobility forecasting can be performed for autonomous UGVs. Compromised sensor data would lead to lower speeds of operation for autonomous UGVs, or even potential NOGO regions. In this fashion, the VANE can be used as a performance prediction tool.

4 THE REFERENCE AUTONOMOUS MOBILITY MODEL

The introduction of autonomy requires several changes to the NRMM paradigm. For autonomous UGVs, mechanical mobility is no longer the driving factor for determining vehicle mobility. Similarly, a human driver is no longer the key factor for determining performance. In order to predict autonomous mobility, a prohibitive number of major changes would be required in the core NRMM software. The core concepts of the NRMM, in particular the comparison of a vehicle's basic parameters against its operational environment, are still crucial to the mobility modeling process. However, a new tool is needed to capture the effects of autonomy on mobility. The goal of the RAMM is to provide this tool.

To be clear, the RAMM is not an extension of the NRMM; it is a new tool that is built using the NRMM conceptual design. The NRMM is a macro-scale mobility predictor that uses low-fidelity environmental

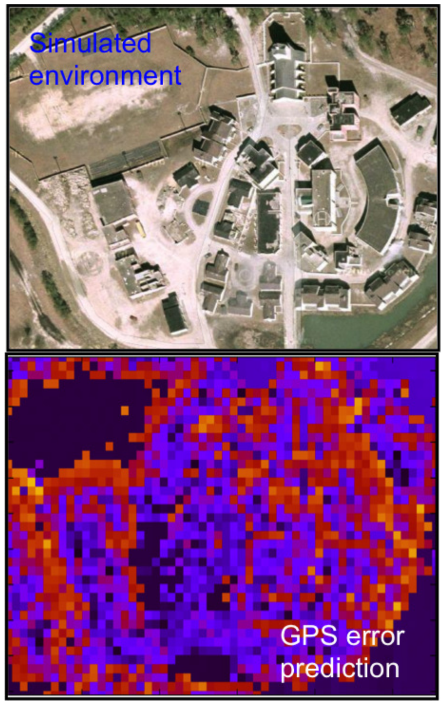

Figure 4: GPS sensor accuracy prediction within a small urban area. The simulated GPS output position was compared with the ground-truth sensor position within the environment to determine the positioning error. Warmer colors indicate higher levels of GPS positioning error.

data as input. Autonomous mobility modeling requires studying the outputs of autonomy algorithms, and these algorithms cannot be evaluated without micro-scale, high-fidelity environment information. Just like the NRMM computes vehicle mobility as a function of environment, the RAMM must compute vehicle autonomous mobility as a function of both environment and input sensor data. Unlike the NRMM, highly-detailed simulation environments are needed to simulate these sensor data and integrate these sensor data with autonomy algorithms to model UGV mobility.

Given the need for high-fidelity simulation environments and sensor data, the RAMM is realized using the VANE. The VANE provides both aspects of mobility modeling, mechanical and perceptional. Unlike the NRMM, the RAMM is a deterministic simulation that uses a physics-first approach to generate, at a near-truth level, sensor and mobility model outputs. Rather than comparing lump parameter vehicle and environment files via empirical relationships, the VANE actually simulates a vehicle traversing a terrain. Similarly, the VANE simulates UGV sensors within the simulation environment. Together, these mobility and sensor simulations can be merged into an overall mobility prediction for an autonomous UGV.

The RAMM operates in a manner akin to the NRMM. A UGV vehicle model is compared against the terrain unit, or operational environment, and speed-made-good is computed. However, for the RAMM, this is accomplished by actually simulating the UGV traversing the environment in the VANE to determine mobility. For the RAMM, the environment is characterized by both the mobility hazards and the fidelity of the sensor data available at that terrain unit (see Figure 4). For the vehicle model, the UGV is characterized by both its mobility performance and its on-board sensors and autonomy algorithms. For driver-based concerns, the VANE is used as a pre-processor to simulate the autonomy algorithms within the environment to determine the UGV's autonomy algorithms' performance as a function of input sensor data.

The overall operation of the RAMM closes the loop between the VANE pre-processing for determining autonomy algorithm performance and the VANE sensor performance modeling. This mobility modeling workflow is show in Figure 5. The pre-processing defines autonomy performance as a function of sensor input data. The sensor performance data define the quality of sensor data available. By comparing autonomy algorithm performance against available data, the RAMM can define the overall ability of a UGV to operate across a given terrain unit. To use the above example from Figure 4, the sensor performance modeling shows that a UGV using an algorithm highly dependent on high-fidelity GPS data would either operate at very low speeds or not operate at all in a dense urban area (this example is shown in detail in Section 5). Using specific algorithm performance, the RAMM could go on to determine what these operational speeds would be.

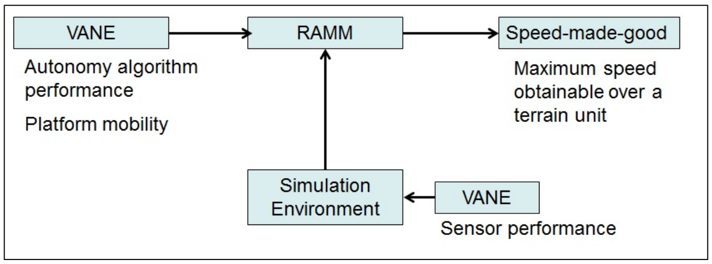

Figure 5: The proposed RAMM workflow. Autonomy algorithm performance is pre-processed, and this characteristic performance is compared against the available sensor data across the environment.

The RAMM will allow for the same types of evaluations performed on manned vehicles as the NRMM performs on autonomous UGVs. For example, the RAMM can be used as a mission planning tool for UGVs. As of writing, the fielding of autonomous UGVs for military applications is limited. One of the hurdles facing autonomous UGV deployment is the inability to understand the mission-level capabilities of these UGVs. By capturing the mobility performance of an autonomous UGV, the RAMM provides mission planners with an understanding of where the UGV can operate and at what speeds it can operate there. This will help in particular in route planning for UGVs.

Another key capability the RAMM will provide is the ability to compare manned vs. unmanned vehicle performance. The trade-off between manned and unmanned vehicles is poorly understood. Difficulties are faced when trying to definitively show the benefits of unmanned vehicles. Difficulties are also faced when trying to determine whether a manned or unmanned vehicle is best for a given mission. The RAMM will provide, via speed-made-good, a snapshot of the performance capabilities of both manned and unmanned vehicles, which allows for an easy comparison between the two.

Furthermore, the RAMM will allow for trade-off studies similar to the ones performed using the NRMM. Rather than looking at performance changes as a function of suspension or tire inflation, the RAMM will allow developers to look at the performance changes as a function of sensors and autonomy algorithms. This will allow decision makers to understand what the benefits of one sensor suite vs. another are or what the relative performance between autonomy algorithms is. This aids in both the requirements writing for and the development of UGV systems.

5 EXAMPLE APPLICATION OF THE RAMM - ROUTE PLANNING WITH GPS SENSOR ATTRIBUTION

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 fairly well understood problem for traditional ground vehicles; however, in the case of autonomous UGVs, additional factors must be considered. The RAMM takes these factors into account by using perception factors in determining operational areas. For this RAMM application, perception was incorporated into the route planning process via environment attribution with GPS sensor accuracy. For this study, a two-km by two-km urban simulation environment was developed for use in the VANE. By simulating a GPS sensor along the road network within this scene in VANE, the accuracy of the GPS sensor outputs was calculated. The relative error in the GPS outputs

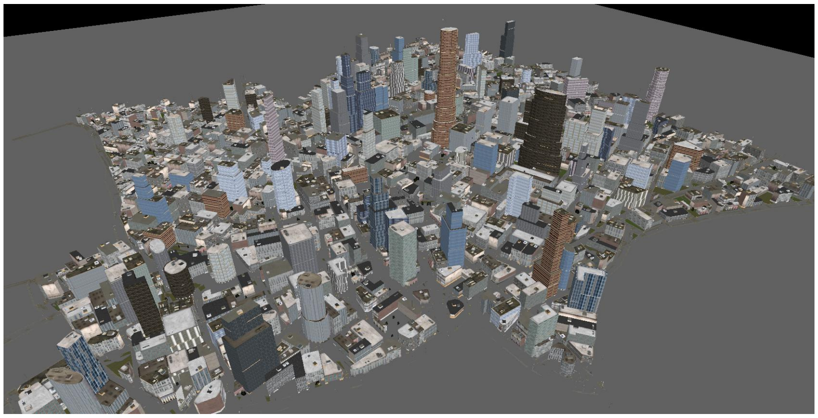

Figure 6: The urban scene developed for use in this study.

were then associated with a cost, and an A* path planner was used to find the lowest cost path across the urban area. This path was compared to the shortest route to highlight the difference in performance between manned and unmanned vehicles.

5.1 Simulating GPS Sensor Accuracy

Figures 6 shows the VANE simulation scene used in this study. The scene chosen was a typical urban cityscape containing approximately 1700 buildings. The urban environment was designed such that it contained many features known to challenge autonomous navigation systems, including urban canyons (narrow roadways surrounded by tall buildings which result in significant GPS dropout). The goal in choosing this scene was to provide a simulation environment that contained areas of both high- and low-quality GPS data.

The GPS sensor error was simulated along a six-meter resolution road network grid at a height of three meters off the ground. To generate the average GPS error values, the GPS was simulated by collecting stationary position data at each grid cell 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 Equation 1.

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

Figure 7 shows the GPS errors along the road network. Each grid cell represents one pixel within the image shown in Figure 7. The x,y axes of pixels in the scene used for this study was run from 0 to 200, with each (x,y) point representing one six-meter by six-meter terrain unit. 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.

5.2 Path Planning using GPS Sensor Accuracy

For manned ground vehicles, path planning uses the A* algorithm, which finds the shortest open path between the start and goal points. Therefore, the natural starting point for this study is the application of A* to the urban road network to determine the base case. Figure 8 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 terrain units and a total path cost of 256.08, where cost is defined as given in (Hart, Nilsson, and Raphael 1968):

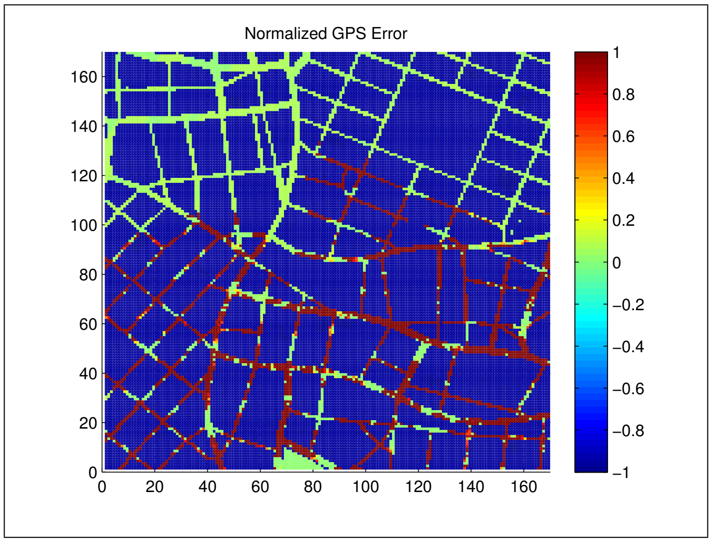

Figure 7: The average GPS error along the road network.

$$f(x) = g(x) + h(x) \tag{2}$$

The path cost function, *g(x)*, can be any function of a node that assigns a positive, real number value to that node (0, in the base case of no GPS error). The heuristic function *h(x)* represents an acceptable estimate of the distance between the node *x* and the goal node.

Next, A* is again applied to the road network grid, only now the GPS sensor errors are added as additional costs to (*g(x)*, to be taken to be the normalized output of Equation 1) to traveling through each grid cell. In this case, A* will return the path with the lowest total cumulative GPS sensor error. A* will also still attempt to follow the shortest path; therefore, the path returned is the shortest path that minimizes GPS sensor error, and not necessarily the path with the absolute minimum total cumulative error.

Figure 9 shows the path chosen for the case of minimizing cumulative errors. From a mobility standpoint, it is a less optimal 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.

Using the VANE as the foundation of the RAMM, the capabilities of the UGV are discovered and quantitatively measured. A UGV that is reliant on GPS data cannot operate in almost 25% of the area of interest. Furthermore, the relative cost of traversing the area is much higher for the GPS-reliant UGV. The RAMM highlights the performance differences between manned and unmanned vehicles and allows decision makers to better plan when and where to deploy autonomous UGVs within this environment. Due to the lack of real-world UGV performance measures, it is not possible at this time to generate a true speed-made-good for this environment. Rather, this example serves to show the general RAMM workflow and performance measuring outputs.

Moreover, the RAMM enables developers to better design their vehicles. The RAMM shows how the GPS sensor accuracy affects mission-level performance. Using the RAMM, a sensor tradeoff study could be performed to observe how changing the inertial navigation solution for the UGV affected UGV performance within the urban environment. A similar study could be performed based on the navigation algorithms used by the UGV. Much as characteristics such as tire inflation and suspension type could be varied to study mission-level performance using the NRMM, characteristics such as sensors and algorithms can be varied using the RAMM.

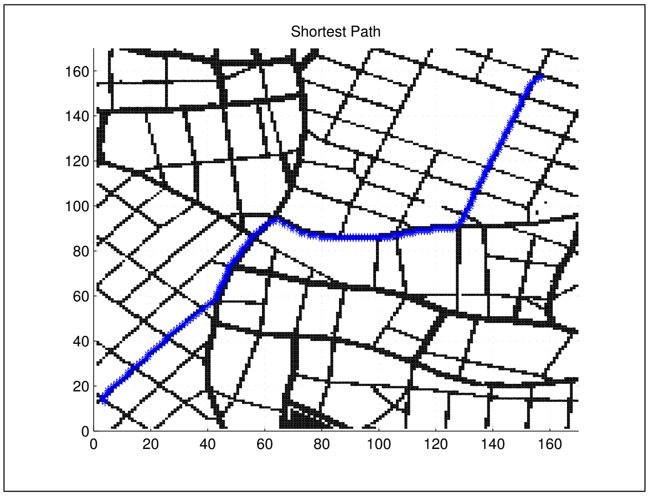

Figure 8: The shortest possible path between the start and goal points within the scene. This path represents the base-case optimal path in the case of zero sensor errors or mobility hazards.

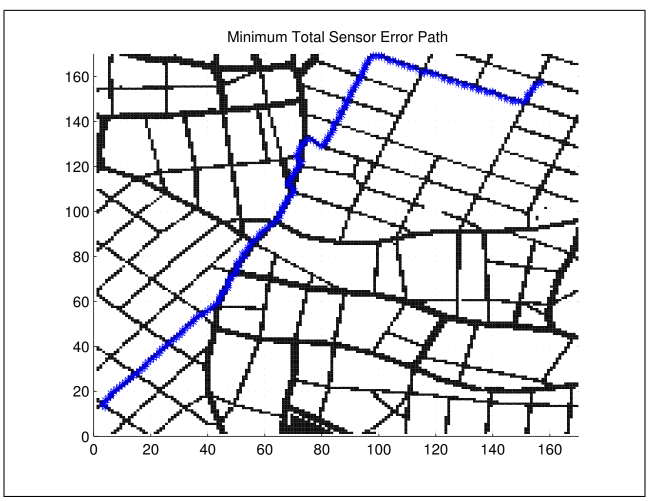

Figure 9: The path between the start and goal points with the lowest total cumulative GPS output errors. From a mobility standpoint, this path is sub-optimal.

6 CONCLUSIONS

Ground vehicle mobility modeling has played a critical role in the vehicle acquisition process. Modeling tools that capture vehicle performance at an operational level are integral in the design, development, testing, evaluation, and fielding of ground vehicles. Since the 1970s, one of the primary vehicle modeling tools in use has been the NRMM. By providing speed-made-good predictions for ground vehicles, the NRMM has provided important information on mission-level performance to both users and developers.

However, NRMM cannot model the mobility of autonomous ground vehicles. Its focus is on mechanical mobility and driver-based concerns. Recognizing the need for a new mobility modeling tool, this paper presented the RAMM, which is the first mobility modeling tool proposed for measuring autonomous mobility. The final outputs of the RAMM is a marriage of the mechanical and perceptive mobility of the UGV.

Like the NRMM, the RAMM will be used for two primary purposes, i.e. showing the impacts of design changes on mission performance and helping mission planners understand the capabilities of an autonomous UGV. The main factors influencing mission performance are sensor and autonomy algorithm performance. The test case presented illustrates how the RAMM can be used in an autonomous urban routing example. By attributing the environment with sensor performance data, a GO/NOGO map for an urban terrain was built using perception data. This analysis showed the performance differences between a manned and unmanned vehicle and also showed the operational performances capabilities of an autonomous UGV that was reliant on high-quality GPS data.

The presented example was created using the VANE. The core operation of the RAMM is to compare autonomy algorithm performances measured using the VANE with the fidelity of sensor data available to these autonomy algorithms across the simulation environment's terrain. Future RAMM development will focus on integrating autonomy algorithms with the VANE and developing the analysis techniques needed to accurately predict autonomous mobility. Once completed, the RAMM will provide the community with the mobility modeling tool it needs as part of the UGV acquisition process.

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