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AUTONOMY MODELING AND VALIDATION IN A HIGHLY UNCERTAIN ENVIRONMENT

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ABSTRACT

This paper describes a simulation model for autonomous vehicles operating in highly uncertain environments. Two elements of uncertainty are studied – rain and pedestrian interaction – and their effects on autonomous mobility. The model itself consists of all the essential elements of an autonomous vehicle: Scene - roads, buildings, etc., Environment - sunlight, rain, snow, etc., Sensors - gps, camera, radar, lidar, etc., Algorithms - lane detection, pedestrian detection, etc., Control - lane keeping, obstacle avoidance, etc., Vehicle Dynamics – mass, drivetrain, tires, etc., and Actuation - throttle, braking, steering, etc. Using this model, the paper presents results that assess the autonomous mobility of a Polaris GEM E6 type of vehicle in varying amounts of rain, and when the vehicle encounters multiple pedestrians crossing in front. Rain has been chosen as it impacts both situational awareness and trafficability conditions. Mobility is measured by the average speed of the vehicle. This work is part of MDAS.ai, a multi-disciplinary autonomous shuttle development project.[2]

1. INTRODUCTION

The U.S. Army is heavily vested in Autonomy [1] and Autonomous Ground Resupply (AGR) - an improved distribution system that involves equipping existing military ground vehicles with scalable robotic technology/capability - is a U.S. Army autonomous vehicles program [2, 3].

Clearly, when these vehicles go through urban terrain, there are impediments to autonomy. The highly uncertain environment that is typical of a congested urban setting, negatively impacts autonomy assurance - population (pedestrians with unknown intent), traffic, non-trafficable roads and weather; not to mention conditions deliberately caused by hostile actors. Even when vehicles are manually driven these are formidable challenges, but when full autonomy is added to the equation, the risk to mobility increases discernably. This

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multi-layered detriment of the autonomy-mobility equation, is a significant scientific challenge [2].

Success in studying this problem has payoffs across at least three military applications - urban operations (UO), manned-unmanned teaming (MUM-T), and AGR. In all these applications, mobility will be positively impacted. There have been several in-depth efforts to study the problem at hand [4-6, 17-20]. Our research adds to this excellent knowledge base, while it also attempts to fill some of the gaps in existing work, specifically the effects of weather and dynamic obstacles on autonomy.

The rest of this paper discusses the following-

a. The computer model covering the scenarios of the mobility problem at hand, and ensuring scalability according to the urban environment it is used in.

b. Test and validation results of the computer model against real world data

c. Quantification of mobility for the problem at hand. Namely, mission speed/time as a function of trafficability and/or situational awareness.

2. AUTONOMY MODELING

The simulation model developed in this paper is derived from the commercial software simulation package PreScan. As explained earlier, the model consists of all the essential elements of an autonomous vehicle:

- *Scene* - roads, buildings, etc.
- *Environment* - sunlight, rain, snow, etc.
- *Sensors* - gps, camera, radar, lidar, etc.
- *Algorithms* - lane detection, pedestrian detection, etc.
- *Control* - path following, lane keeping, obstacle avoidance, etc.
- *Vehicle Dynamics* - mass, drivetrain, tires, etc.
- *Actuation* - throttle, braking, steering, etc.

In the rest of this section we describe each of these elements.

2.1 Autonomy modeling: Scene

Our simulation includes a 3-D model of the scene – roads, lane markers, traffic signs, cross-walks, side-walks, and buildings form the core of the scene component of the model. Fig.1 captures a visual representation of the 3-D scene model – a segment of the University of Michigan-Dearborn 1.75 mile campus loop. The model was built using SketchUp [22], and validated online information sources such OpenStreetMap [21]. Model dimensions were verified against ground truth.

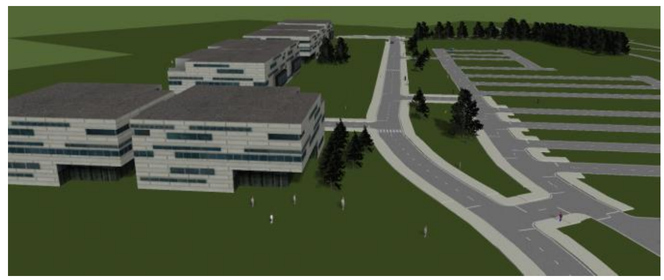

Figure 1: 3-D model of UM-D campus loop segment.

2.2 Autonomy modeling: Environment

The environment alters the way the scene is perceived and navigated. For example, extreme rain or snow will appreciably decrease both the situational awareness and trafficability of a scene. Our simulation models such environmental effects - Fig. 2 captures the difficulty in perceiving a scene due to weather conditions.

Figure 2: Decrease in situational awareness due to extreme snow.

2.3 Autonomy modeling: Sensors

The MDAS.ai vehicle has multiple sensors, operating in multiple modalities – high-def cameras (perception), gps (positioning), radar (all-weather), lidar (ranging), etc. The technical specifications of these sensors, as well as the effects on viewing geometry (depending on how they are mounted on the vehicle) are all considered. Fig. 3 captures a screenshot of the camera model within our simulation. These models have been long studied and validated at TNO [23-25].

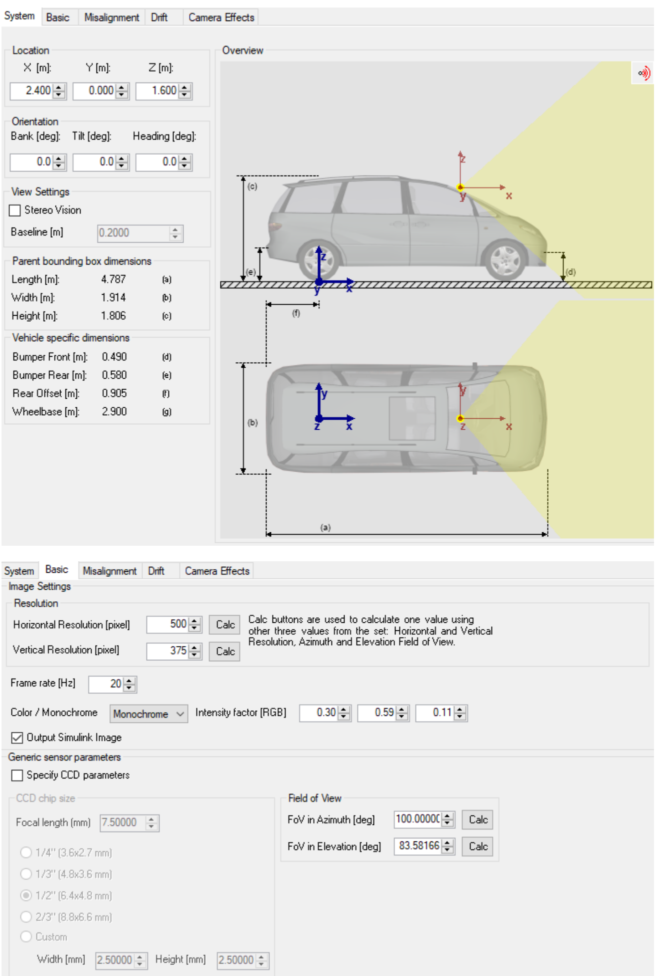

Figure 3: Camera model that includes both component-level effects as well as system-level effects.

Other sensors are similarly modeled.

2.4 Autonomy modeling: Algorithms

The authors have worked on perception algorithms for the purpose of enabling autonomy in vehicles for more than 25 years. References [7-10] pertain to some of the widely referenced papers in this area. The simulation model presented in this paper incorporates similar algorithms. The output from these algorithms create a binary map of the perceived scene as shown in Fig. 4.

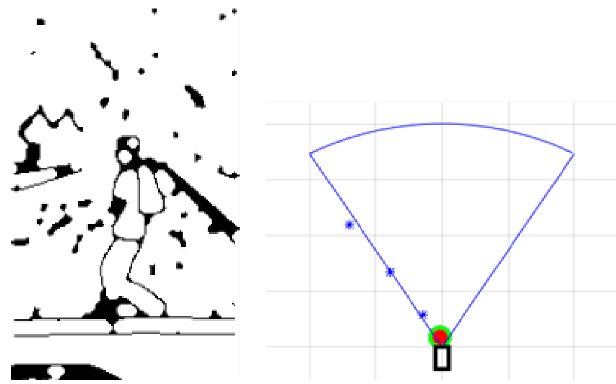

Figure 4: Perception of lane markers and objects including pedestrians, vehicles, buildings, etc.

2.5 Autonomy modeling: Control

The MDAS.ai vehicle has three low-level control tasks, namely, path following, lane keeping, and obstacle avoidance. References [11-14] describe the control schemes. Fig. 5 shows the control steps involved in avoiding collision with a pedestrian.

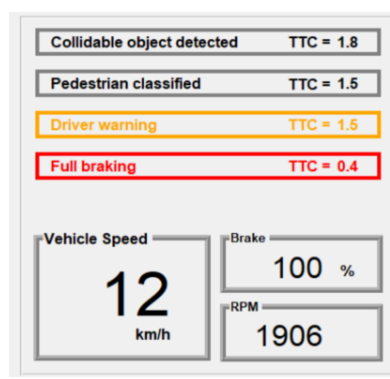

Figure 5: Detect → Classify → Warn → Brake steps in collision avoidance control.

2.6 Autonomy modeling: Dynamics

MDAS.ai uses a Polaris GEM E6 vehicle. The dynamics of this vehicle is approximated in the model using CarSim [26-27], including the vehicle mass, dimensions, drivetrain, tires, etc. Fig. 6 captures the said dynamics.

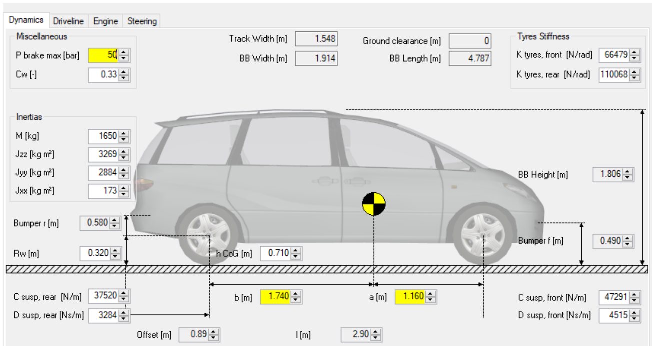

Figure 6: Approximation model of the Polaris GEM E6 vehicle dynamics.

2.7 Autonomy modeling: Actuation

The final step to autonomous control of the MDAS.ai vehicle is actuation – throttle, brake, and steering being the three basic ones [26-27]. Fig. 7 captures the actuation block in the simulation.

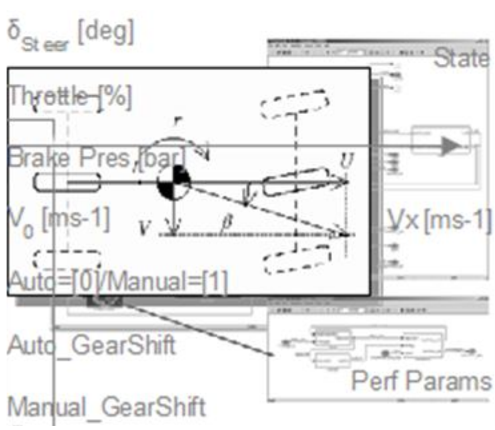

Figure 7: Approximation model of the Polaris GEM E6 vehicle actuation.

3. SIMULATION RESULTS

Our simulation was focused on measuring the effects on autonomous mobility due to changes in trafficability and situational awareness. This problem is of significant interest to the U.S. Army [2].

To change trafficability and situational awareness, we used the following element of our simulation - *Autonomy modeling: Environment* (see Section 2.2). We introduced rain of varying rate into the scene environment, and measured its effects on trafficability, situational awareness, and finally autonomous mobility. We have quantitative results to report.

As rainfall increases, the perception of lanes and obstacles in the environment becomes more difficult, thereby the task of detecting and classifying lanes and obstacles in the environment takes a longer time to complete [15]. We have measured the relationship between rain rate and time for perception and it is captured in Fig. 8.

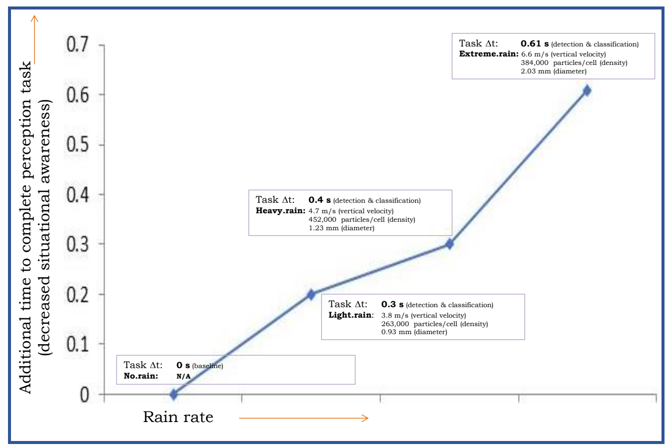

Figure 8: Quantifying decreased situational awareness due to increased rain rate (mean of 70 runs).

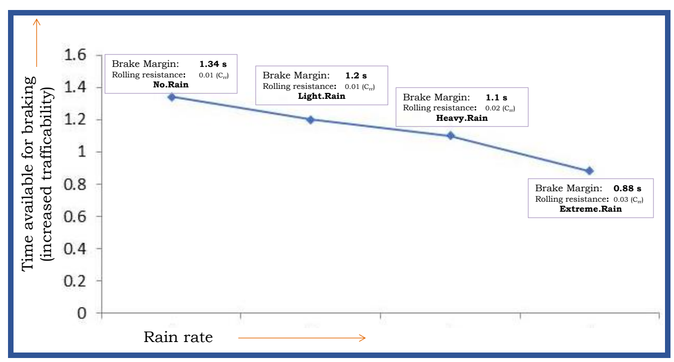

Figure 9: Quantifying decreased trafficability due to increased rain rate (mean of 70 runs).

Similarly as rainfall increases, vehicle deceleration for the same brake pressure decreases, thereby decreasing the time-to-collision

(TTC) [16]. We have measured the relationship between rain rate and the resulting decrease in time available for braking, and it is captured in Fig. 9.

Finally, we capture the changes in autonomous mobility due to changes in trafficability and situational awareness [2]. For this, we introduce multiple dynamic pedestrians into the scene. The trajectory of these pedestrians was chosen to intersect that of the autonomous vehicle. Ideally, if the vehicle and the pedestrians are able to maintain their set velocities, only two of these pedestrians would pass exactly in front of the vehicle during the simulation run. The vehicle is simulated to perceive these pedestrians, and stop at a safe distance to allow them to pass. However, if the vehicle takes a longer than expected time to perceive and brake (lowering the average speed), such as when the rain rate increases, more of these dynamic pedestrians would pass in front of the vehicle, thereby further lowering the average speed. This effect is captured in Fig. 10, and it clearly shows that autonomous mobility decreases with increasing rain rate.

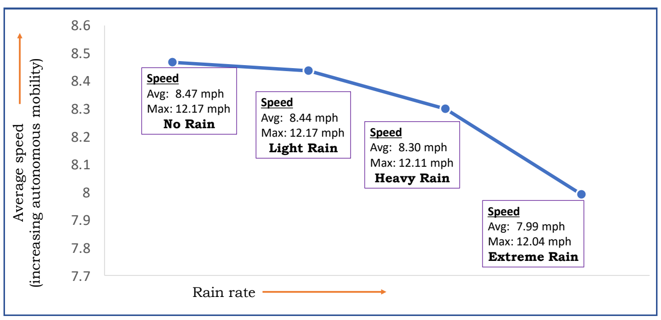

Figure 10: Quantifying decreased mobility due to decreased situational awareness and trafficability (mean of 70 runs).

Figures 8, 9, and 10 confirm the relationships between autonomous mobility versus situational awareness and trafficability [15-16], and they report the mean of 70 simulation runs.

4. FUTURE WORK

The ultimate of MDAS.ai is a Level-3 or above autonomous shuttle operating on the campus of the University of Michigan-Dearborn (1.75 mile loop shown in Figure 11).

Figure 11: The 1.75 mile campus loop for MDAS.ai

The (commuter) campus loop presents highly uncertain environment for autonomy – pedestrian rich, lots of cross-traffic, and construction-related impediments. Our simulation effort is focused on high-fidelity modeling, and quantitatively measuring the effects of various factors on autonomous mobility, including safety and reliability. These factors include sensors, actuators, algorithms, and vehicle communications. We expect to report more results on this simulation effort in our future publications.

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