Quantifying the Effects of Environmental Conditions on Autonomy Algorithms for Unmanned Ground Vehicles

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Abstract. Autonomy for commercial applications is developing at a rapid pace; however, autonomous navigation of unmanned ground vehicles (UGVs) for military applications has been deployed to a limited extent. Delaying the use of autonomy for military applications is the environment in which military UGVs must operate. Military operations take place in unstructured environments under adverse environmental conditions. Military UGVs are infrequently tested harsh conditions; therefore, there exists a lack of understanding in how autonomy reacts to challenging environmental conditions. Using high-fidelity modeling and simulation (M&S), autonomy algorithms can be exercised quickly and inexpensively in realistic operational conditions. The presented research introduces the M&S tools available for simulating adverse environmental conditions. Simulated camera images generated using these M&S tools are run through two typical autonomy algorithms, road lane detection and object classification, to assess the impact environmental conditions have on autonomous operations. Furthermore, the presented research proposes a methodology for quantifying these environmental effects.

Key words: Autonomy, Autonomous Ground Vehicles, Environment Effects, Perception

1 Introduction

Autonomy for commercial ground vehicle applications is enjoying a great deal of success in the field, such as the Google car or Tesla[1]. However, autonomy for military ground vehicles has lagged far behind industry. While several factors have led to this lag, one primary obstacle to military autonomy applications is the operational environment. While commercial applications have the luxury of operating in stable, benign environments, military applications take place in harsh and unpredictable conditions. Autonomy algorithms, which are by nature often shown to be susceptible to the operational environment[2], often fail in harsh conditions, such as rain, snow, and fog. Moreover, little research has been given over to understanding exactly how such environmental conditions impact autonomous operations. Rather, autonomous ground vehicles remain tested and fielded primarily in the case of predictable, known, on-road conditions.

The effects of adverse weather on autonomy are not understood or, to date, measured in a quantitative fashion. Human driver response to rain, dust, soft soil, etc. can be empirically measured and modeled. However, sensor / autonomy responses to these conditions require complex data acquisition that is difficult and expensive to recreate in the field. The goal of this paper is to demonstrate how high-fidelity simulations can be used in lieu of field testing and that the controlled and repeatable conditions achieved in simulation can enable the development of quantitative metrics for algorithm performance.

The paper is laid out as follows. Section 2 gives a brief introduction to the simulation software used in this study, Section 3 provides example evaluations of algorithm performance as a function of environment. Specifically, performance is assessed for both a lane detection algorithm operating in ideal and heavy rain situations and an object classification computational neural network (CNN) algorithm at varying times of day. Lastly, Section 4 provides concluding thoughts and recommendations for future work.

2 VANE: High-fidelity Modeling and Simulation for Autonomous UGVs

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 unmanned ground vehicles (UGVs) [3] [4]. VANE originated as a tool 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 [5] [6]. As such, VANE is a micro-scale, mission-level simulation tool for performance assessment and algorithm development for autonomous UGVs.

There are several key components to VANE, the most important of which is the sensor and environment models that are used in the development and testing of autonomy algorithms. On top of the sensor modeling are the mobility and vehicle dynamics models. These mobility and sensor models together recreate the physical behaviors of the UGV as it reacts to its autonomy algorithms. This study focuses on sensor-environment interactinos as they impact autonomy algorithms, and therefore VANE's mobility models are not discussed further in this paper. Further details of VANE's sensor-environment models are given below.

The core of 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, VANE can more accurately simulate autonomous UGV 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 [7] bidirectional relectance distribution function (BRDF) model for surface reflectance. The atmosphere in VANE is also modeled using a physics-first approach and implemented using numerical methods found within literature [8] [9].

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 1 shows an example VANE geo-environment. Coupled to the environment model are the sensor models. The VANE contains models for the sensors most commonly used by autonomous UGVs, e.g. camera, LIDAR, and GPS sensors, and Figure 2 shows an example simulated sensor output for a CCD camera.

3 Algorithm Performance Under Varying Environmental Conditions

While it is well known qualitatively that adverse environmental conditions negatively impact autonomy algorithm performance, this degradation of performance has yet to be studied in a quantifiable way. Common sense shows that image processing algorithms will be less effective in the rain, and it has been shown in literature that rain reduces the performance of image processing algorithms [15] [11]. Similarly, the difficulties image processing algorithms suffer when operating at dusk or dawn are well-known qualitatively [12]. The goal of this paper is to take these phenomena and leverage simulation to quantify performance as a function of environment for two popular navigation algorithms: object classification and lane detection.

3.1 Object Classification via CNN

CNNs can achieve reasonable performance on hard visual recognition tasks, sometimes matching or even exceeding human performance in some domains. Inception-v3 is a CNN that was trained for the ImageNet Large Visual Recognition Challenge. The CNN was developed using TensorFlow, which is an open-source software library for machine learning developed by the Google Brain team. To compare models in the ImageNet Large Visual Recognition Challenge, it is common practice to examine how often the model fails to predict the correct answer as one of its top five guesses termed top-5 error "rate" [13]. Inception-v3 reached a 3.46% top-5 error rate for the ImageNet Large Visual Recognition

Fig. 1. An example VANE environment of a forested area.

Fig. 2. An output image from a Sony CCD camera compared with the real object being modeled within the geo-environment.

Challenge using the data from 2012 while AlexNet achieved a 15.3%, Inception [?] achieved a 6.67%, and BN-Inception-v2 achieved a 4.9%. Since a pre-trained CNN was used in this study, the number of nodes was constrained to 90,000; therefore, the images had a size limit of 300 by 300.

Modern object recognition models contain a large number of parameters that can take long periods of time to fully train. This study uses a transfer learning technique to shortcut the training time by taking the fully-trained Inception-v3 model and retraining from the existing weights for new classes. The final layer is retrained from scratch, while leaving all the other layers untouched. The premise behind this idea is that the natural phenomenon of interest tends to have a hierarchical structure that deep neural networks naturally capture. At the lowest layers of the neural network, simple things such as lines and edges are detected and fed to higher layers for detecting more complex things, such as part shapes. The last layer of the neural network combines all parts together to detect objects of interest.

Several methods, such as deforming, cropping, or brightening the training inputs, were available and utilized for improving the results of image training in random ways. These methods have the advantage of expanding the effective size of the training data due to all of the possible variations of the same image and tends to help the network learn to cope with all the distortions that will occur in real-life uses of the classifier [13].

For this particular study, the CNN was used as a binary classifier for detecting a Heavy Expanded Mobility Tactical Truck (HEMTT). The VANE-generated imagery was used for the simulated data. The simulated data consisted of 1,871 images in an urban environment and 1,630 images in a rural environment with half of the images in a clear condition and the other half of the images in a hazy condition. The time of day was varied from 0900 to 1700. The camera views of the vehicle were randomly chosen for a 360 horizontal view of the vehicle with a maximum angle of 45 from the ground.

To evaluate the performance of the CNN, the neural network was given simulated data from a camera in a forest environment under varying rainfall rates and at different times of day, which could be set using VANE's simulation environment. The Figure 3 below shows the impact of the rainfall rate on the CNNs ability to detect the HEMTT vehicle in the form of confidence of detection vs rainfall rate. Figure 4 shows a sample simulated image with rainfall. Probability of detection was not performed because probability of detection requires a large diverse data set for each rainfall rate to get a good measurement of the CNNs probability of detecting the vehicle. In this work, a single data set consisting of images with increasing rainfall rate was evaluated for proof of concept of the degradation of performance of the CNNs confidence in detection with respect to rainfall rate using simulated data.

Similarly, Figure 5 shows the impact of time of day on detection confidence. The same image set of a HEMTT in a forested setting was used for training. The trained CNN was then tested on images over the course of a 24 hour day. It this study, the HEMTT was aligned east to west, so that at dawn the sun

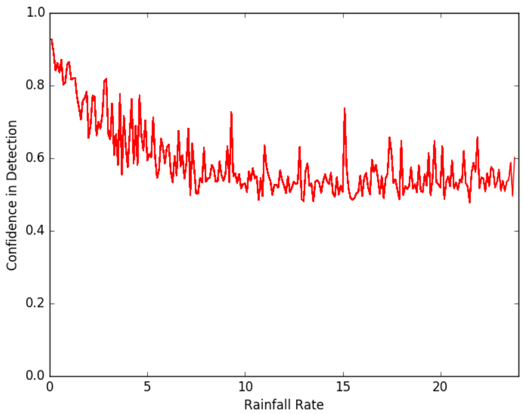

Fig. 3. The confidence of detection vs rainfall rate for the HEMTT in rain.

Fig. 4. An example simulated camera image of the HEMTT in rain.

was directly behind the vehicle and at dusk the sun was shining directly unto the vehicle. Figure 6 shows a sample simulated image at dawn. Figures 3 and 5 show, and quantify, the environmental affects long known to hinder autonomy. Furthermore, by showing these effects quantitatively, objective performance of algorithms can be undertaken and algorithms can be compared rigorously for optimal performance.

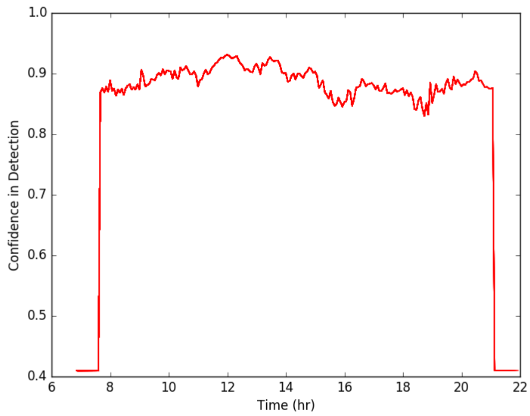

Fig. 5. The confidence of detection vs time of day for the HEMTT.

3.2 Lane Detection

A key task that must be accomplished for on-road autonomous navigation is lane detection. For a ground vehicle to successfully follow a road, it must know the physical characteristics of said road, namely the width and curvature. Therefore, much research has been given to developing these algorithms, which are in use already for many commercial applications. However, little effort has been given over to quantifying these algorithms performance in adverse environmental conditions, and therefore these algorithms are typically not used in rain / snow / fog etc..

This is not to say that lane detection alrgorithms are never deployed in these challenging conditions. Several filters and other image processing techniques can be used to reduce the noise created by rain for lane detection algorithms, and details on these methods can be readily found in [15]. However, for the purposes of this study, a simple algorithm with no noise reduction was chosen. The reason for this choice is that this study does not aim to test a specific algorithm but rather to benchmark this particular type of algorithm's performance. The quantities measured below reflect a "base-line" performance and define a general operational envelope as a function of environmental conditions.

Fig. 6. An example simulated camera image of the HEMTT at dawn.

The chosen lane detection algorithm was tested against two sequences of simulated images: one under clear sky conditions and one in "heavy" rain condition of a rainfall rate of 20. This study quantifies lane detection performance in two ways. The first is percent detection. This metric is the number of frames with lanes detected divided by the total number of frames analyzed by the algorithm. For this study, 37 images were simulated, and the accuracy of the algorithm in clear and raining conditions can be found in Table 1. Table 1 also shows the average accuracy of the detections calculated as given below.

Accuracy of detection was taken as the magnitude of the differences between the ground truth slopes of the lanes in the image and the slopes of the detected lanes. As Table 1 and Figures 7 and 8 show, a significant drop in accuracy was observed in the raining condition.

Figure 8 shows the output of the lane detection algorithm on an image taken by the camera sensor in the "heavy" rain condition. On the other hand, Figure 7 shows the output for the same image on a clear day. Qualitatively, the algorithm clearly fails in the rain; however, using the methods described above, this failure can be quantified. In so doing, the accuracy of the "heavy" rain image is only 43.6%, whereas the accuracy of the "clear" image is 98.7%.

Table 1. Lane detection algorithm performance comparison between clear and heavy rain conditions.

condition	percent of frames with detection	average detection accuracy
heavy rain	81.1%	72.5%
clear	91.2%	94.7%

Fig. 7. An example simulated camera image with lanes detected under clear sky condition.

Fig. 8. An example simulated camera image with lanes detected under "heavy" rain condition.

4 Conclusions

The future military and commercial vehicle fleets will almost certainly have some form of autonomy-enabled operations. Even manned vehicles are likely to have on-board algorithms to enable operators to perform at a higher level. To date, unmanned ground vehicles have not been fielded for military applications beyond experimental systems and limited testing. This lack of application is due in large part to the complexity of the operational environment for UGVs. Systems must be able to operate not only in unstructured and unpredictable environments but also operate in these environments in adverse environmental conditions. To push the envelope of operations for UGVs, a more comprehensive understanding of the impact environment has on autonomy is necessary.

To meet this need, this paper proposed and presented a method for quantitatively assessing autonomy performance as a function of environmental conditions. This study took two test cases: rainfall and time of day, and two algorithms: object classification and lane detection. Using high-fidelity M&S, the environmental conditions were fully controllable, which enabled consistency in experiments and well-defined environmental conditions. Using these benefits of M&S, data was collected in the form of simulated camera images, and algorithm performance was studied.

The findings of this study reflect the qualitative knowledge already contained in the autonomy community: rainfall degraded algorithm performance for both object classification and lane detection, and time of day degraded performance of object classification. The major impact of this study was to quantitatively measure these impacts. In so doing, algorithm developers will now have a means for objectively assessing algorithm performance, which will in turn enable more robust algorithm development. Furthermore, these quantitative assessments will enable better comparisons between algorithms to determine which algorithm is best suited to which environment. Leveraging M&S for these types of studies and expanding test cases to additional sensors, environments, and algorithms will allow for faster and more robust development of future autonomy for military applications.

Acknowledgments. Permission to publish was granted by Director, Geotechnical and Structures Laboratory.

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