

NIR Sensitivity Analysis with the VANE

Justin T. Carrillo^{*a}, Christopher T. Goodin^a, Alex E. Baylot^a

^aU.S. Army Corps of Engineers - Engineer Research & Development Center, 3909 Halls Ferry Rd, Vicksburg, MS, USA 39180

ABSTRACT

Near infrared (NIR) cameras, with peak sensitivity around 905-nm wavelengths, are increasingly used in object detection applications such as pedestrian detection, occupant detection in vehicles, and vehicle detection. In this work, we present the results of simulated sensitivity analysis for object detection with NIR cameras. The analysis was conducted using high performance computing (HPC) to determine the environmental effects on object detection in different terrains and environmental conditions. The Virtual Autonomous Navigation Environment (VANE) was used to simulate high-resolution models for environment, terrain, vehicles, and sensors.

In the experiment, an active fiducial marker was attached to the rear bumper of a vehicle. The camera was mounted on a following vehicle that trailed at varying standoff distances. Three different terrain conditions (rural, urban, and forest), two environmental conditions (clear and hazy), three different times of day (morning, noon, and evening), and six different standoff distances were used to perform the sensor sensitivity analysis. The NIR camera that was used for the simulation is the DMK firewire monochrome on a pan-tilt motor.

Standoff distance was varied along with environment and environmental conditions to determine the critical failure points for the sensor. Feature matching was used to detect the markers in each frame of the simulation, and the percentage of frames in which one of the markers was detected was recorded. The standoff distance produced the biggest impact on the performance of the camera system, while the camera system was not sensitive to environment conditions.

Keywords: Virtual Autonomous Navigation Environment, near infrared, sensitivity analysis, environmental conditions, object detection, DMK firewire monochrome, sensor modeling, environmental modeling

1. INTRODUCTION

The Virtual Autonomous Navigation Environment (VANE) is a high-fidelity, physics-based simulation software that produces realistic simulated sensor output for use in the development and testing of manned and unmanned ground vehicles¹. The VANE integrates simulations of sensors, vehicle dynamics, terrain mechanics, and environmental conditions and utilizes physics-based sensor, thermal, vehicle-terrain interaction, groundwater, and reflectance models. Core products of the VANE simulate geoenvironmental influences on sensor responses and vehicle dynamics to predict robotic behavior in a given environment². VANE has been used for closed-loop system analysis for reconnaissance missions using autonomous routing, drive, and surveillance³; pedestrian detection using Light Detection and Ranging (LIDAR); sensor error predictions for route planning⁴; optimal camera placement by evaluating probability of detection versus look ahead distance⁵; and currently applying advanced leader/follower autonomy to multiple tactical vehicle types that serve in convoys. The purpose of the near infrared (NIR) sensitivity analysis was to set up VANE simulations to measure the environmental effect on performance of a camera system in detecting an active fiducial marker. Three different terrain conditions (rural, urban, and forest), two environmental conditions (clear and hazy), three different times of day (morning, noon, and evening), and six different standoff distances along with four different camera resolutions were used to perform the sensor sensitivity analysis.

2. TESTING SETUP AND ENVIRONMENTAL CONDITION

In the VANE simulation, we evaluated the ability of a NIR camera to detect a marker on the rear of a lead vehicle. The marker can be used to determine the relative position of the lead vehicle with respect to the following vehicle. A vehicle was simulated with VANE using an active fiducial marker attached to the rear bumper of the vehicle. Image processing in MATLAB was used to find the marker for each image generated by the VANE. To determine critical failure points for the camera sensor in a variety of environments and conditions, the time of day, atmospheric parameters, and camera resolution were given various input parameters. In VANE, the time and location of the scene can be specified using parameters such as latitude, longitude, time zone, date, and time; the VANE will automatically position the sun correctly and calculate the UTM offset⁶. The morning, midday, and evening times for the simulations were chosen to be 07:30, 12:00, and 18:30, respectively, while all other parameters specifying the date, time, and location were held constant. Figure 1 below shows images for the midday and evening times of day for the urban scene. The RGB images in the paper are presented for visibility of the scene, environmental conditions, terrain conditions, and times of day and are not the NIR images used for the sensitivity analysis. Figures 4 and 5 show examples of the NIR images that were used in the sensitivity analysis.



Figure 1. Midday (left) and evening (right) times of day

The inputs for camera models in the VANE require the number of horizontal pixels, number of vertical pixels, number of bands in the imaging system, size of the horizontal side of the Complementary Metal Oxide Silicon (CMOS) or Charge Couple Device (CCD) pixel array, size of the vertical side of the CMOS or CCD pixel array, and focal length of the lensing system⁶. The parameters chosen to best match the DMK firewire monochrome NIR camera are given in Table 1 below. The camera resolution was also varied from 384 by 512 to 1536 by 2048 to observe the impact of resolution loss and gain on object detection.

Table 1. DMK Firewire Monochrome NIR Camera Input Parameters

Camera Resolution	768 x 1024
# of bands	1
Size of horizontal side of pixel array	6.656 mm
Size of vertical side of pixel array	4.92 mm
Focal length	45.0 mm

The atmospheric parameters of a simulation affect the propagation of radiant energy that influence LIDAR and Camera sensors⁶. For particle systems like dust and rain, more input parameters, such as size, drag, transparency, and diffusion of the particles, are required. As with all many-body systems in computing, the dusty and rainy environmental conditions have a major impact on simulation time; therefore, the dusty and rainy environmental conditions were only simulated for certain terrains. Images for all four conditions produced by the VANE are given in Figure 2 below for the Forest Service Road forest scene.



Figure 2. Various environmental conditions. Top Left: Haze, Top Right: Clear, Bottom Left: Rainy, Bottom Right: Dusty.

Terrain conditions have a major impact on the ability of a camera system to detect a marker on the rear of a leading vehicle as well as the impact on the vehicle dynamics of the vehicle. Three different terrain conditions were evaluated for the NIR sensitivity analysis using geo-specific and geo-typical scenes. Geo-specific scenes are built with ground truth attributions for reflectance, soil strength, and scene geometry, while geo-typical scenes are built using a library of materials⁷. The three different terrain conditions are shown in Figure 3. Marine Corps Base Camp Lejeune in Jacksonville, North Carolina was used as the geo-specific rural scene for the simulations, and the Forest Service Road at the Engineering Research and Development Center (ERDC) in Vicksburg, MS was used as the geo-specific forest scene. The geo-typical urban scene was built from libraries of materials. The urban scene consisted of four square kilometers of dense urban terrain and took approximately two hours to generate 209 images. The Camp Lejeune rural scene consisted of 632 objects and took approximately one hour to generate 155 images. The Forest Service Road forest scene consisted of 15,074 objects and took approximately two hours to generate 116 images. All scenes were simulated using 32 supercomputer nodes that contained 32 processors for a total of 1.024 processors.



Figure 3. Various terrain conditions. Top Left: Urban, Top Right: Forest, Bottom: Rural

The MATLAB routine that was used as the object detection algorithm for the VANE generated images using the detectSURFFeatures function that returns a SURFPoints objects, points, containing information about SURF features detected in the 2-D grayscale input image. The function implements the Speeded-Up Robust Features (SURF) algorithms to find blob features. For key points and point matching, we used the SURF descriptor, one of the most commonly used image descriptor in recent years in computational imaging⁸. Image descriptors and features matching are both rather noisy processes; the descriptors are subject to image noise and compression artifacts, and not all presume correspondence are true correspondences due to descriptor error and ambiguities in the matching⁹. SURF is a local feature detector and descriptor that can be used for tasks such as object recognition or registration or classification or 3D reconstruction. It is partly inspired by the scale-invariant feature transform (SIFT) descriptor. The standard version of SURF is several times faster than SIFT and claimed to be more robust against different image transformations than SIFT. To detect interest points, SURF uses an integer approximation of the determinant of Hessian blob detector, which can be computed with 3 integer operations using a precomputed integral image. Its feature descriptor is based on the sum of the Haar wavelet response around the point of interest. SURF is a detector and a descriptor for points of interest in images where the image is transformed into coordinates using a multi-resolution pyramid technique⁸. The object detection algorithm used to detect the marker behind the lead vehicle is shown in Figure 4 for the Camp Lejeune rural scene and in Figure 5 for the Forest Service Road forest scene.

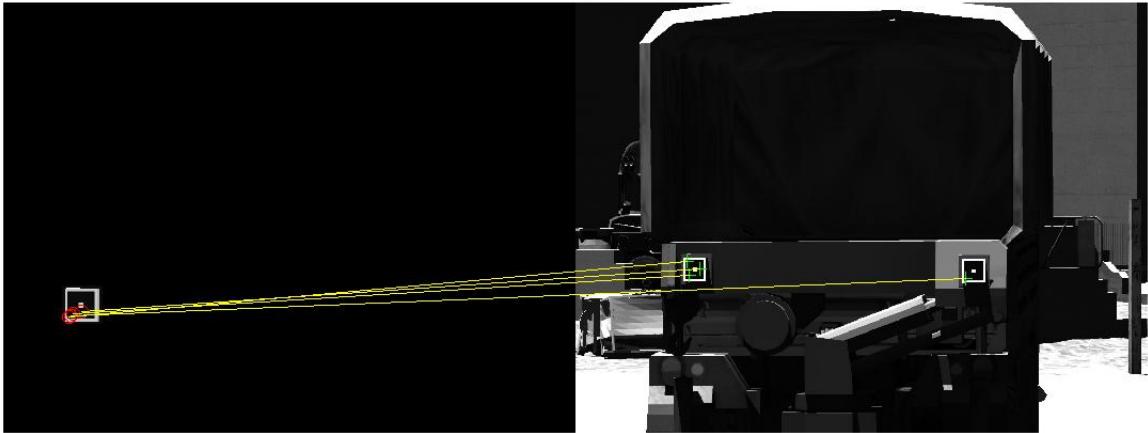


Figure 4. Camp Lejeune key features matched



Figure 5. Forest Service Road key features matched

3. LIMITATIONS OF THE ANALYSIS

There were several computational limitations, time constraints, and pre-processing limitations that provided restrictions to the NIR sensitivity analysis study. Scene size provided a computational limitation by the maximum number of objects that could be presented to accurately represent a real scene. The particle-systems that are used to represent rain and dust in the scenes provided computational limitations in the form of many-body problems. Scene size limited by the amount of memory that objects in the scene require compared to the amount of computer memory that is available on the hardware, while the particle-system is limited by the processing speed on the hardware. The rain and dust environments produced by the VANE were limited by the time constraints of the study and the processing speed of the hardware; therefore, the rain and dust environments are only provided as proof of concepts and not included in the analysis.

The Autonomous Navigation Environment Laboratory (ANVEL) is a Windows-based, desktop, low-fidelity, real-time simulation tool that was used as a pre-processor to the VANE. ANVEL's interactive, user-friendly tools for waypoint navigation and vehicle dynamics allowed for the development of a vehicle replay file that could be easily loaded into a VANE simulation. Path editing was performed via waypoints through ANVEL to incorporate vehicle speed and vehicle dynamics along a user-defined route. This provided a limitation to the study because ANVEL does not contain the high-fidelity vehicle dynamics of the VANE nor the high-fidelity vehicle models that were generated for the VANE. The autonomous waypoint navigation algorithms that are provided in ANVEL were used to keep consistency across the different speeds and terrain conditions and ensure that the same route was used in all parts of the analysis.

An important limitation to note is that the analysis measures performance of the camera system in object detection and does not measure the overall performance of a particular autonomous system. In order to measure the overall performance of a particular autonomous system, the autonomy algorithms would need to be integrated in a closed loop simulation to measure the advanced behaviors of the autonomous system. Also important to note is that the NIR sensitivity analysis measures the critical failure points for the camera and not the optimal environmental conditions, terrain conditions, or time of day for optimal performance.

4. NIR SENSITIVITY ANALYSIS AND RESULTS

The NIR sensitivity analysis using the VANE required a NIR camera that was always aimed at the rear of the lead vehicle. The NIR camera that was modeled was the DMK firewire monochrome NIR on pan-tilt motor. Following distance was varied along with the terrain and environmental conditions. Feature matching was used to detect the markers in each frame of the simulation to provide the percentage of frames in which one of the markers was detected and recorded. Figure 6 shows the percentage of frames detected versus the following distance in meters from the lead vehicle for the Forest Service Road forest scene. There were 107 frames for each simulation and 54 scenarios ran that resulted in 5,778 images generated and analyzed. From Figure 6, it is evident that the clear condition during midday performs the best at being able to detect the marker overall which matches intuition. Also, from the graph, it is observed that there is a steep decrease in performance for distances greater than 120 meters.

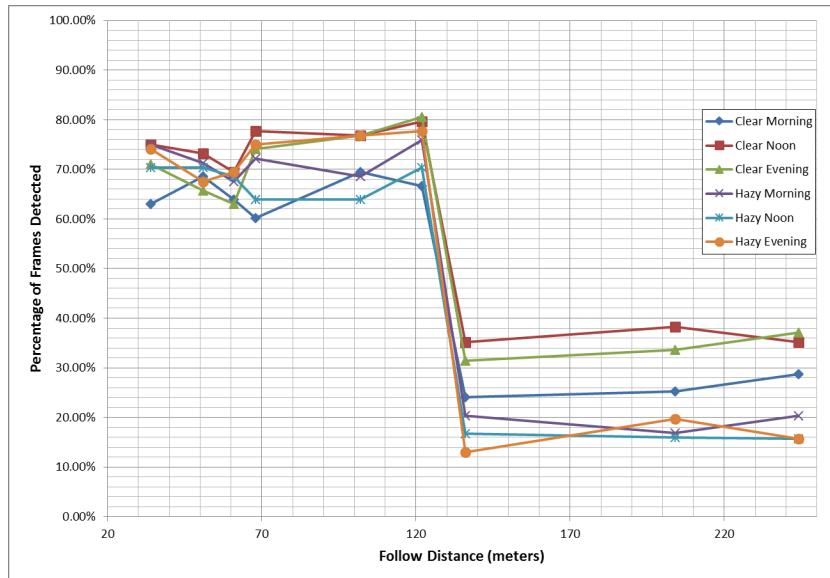


Figure 6. Percentage of frames detected for the Forest Service Road forest scene

For the Camp Lejeune rural scene, there were 135 frames for each simulation and 54 scenarios completed, resulting in 7,290 images generated and analyzed. Figure 7 shows the percentage of frames detected versus the following distance in meters from the lead vehicle for the Camp Lejeune rural scene. The overall shape of the graph is similar to the graph for the Forest Service Road forest scene. Once again, there is a steep decrease in performance for following distances greater than 120 meters.

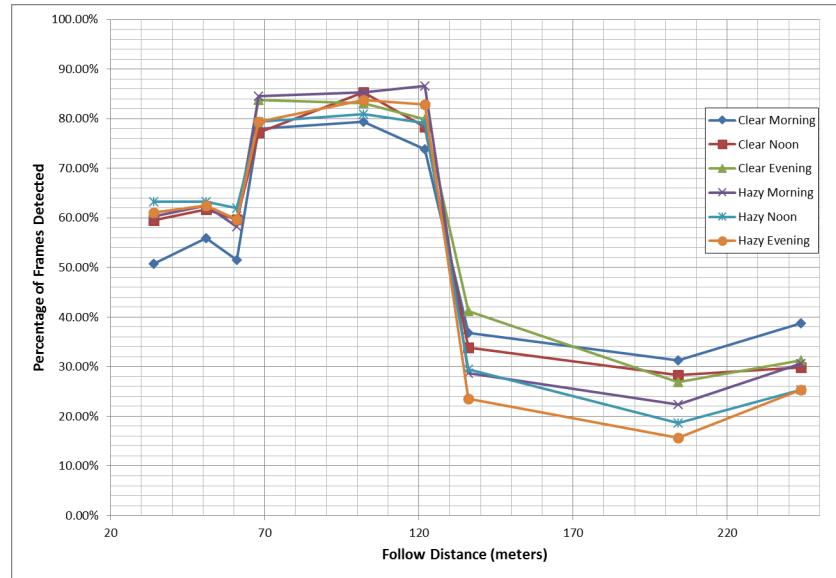


Figure 7. Percentage of frames detected for the Camp Lejeune rural scene

For the Urban scene, there were 99 frames for each simulation and 54 scenarios ran that resulted in 5,346 images generated and analyzed. Figure 8 shows the percentage of frames detected versus the following distance in meters from the lead vehicle for the Urban scene. The graph displays a greater deviation from the shape of the Forest Service Road forest scene and Camp Lejeune rural scene and shows a bigger impact from the environmental conditions compared to following distance than the graphs previously presented. The graph represents the impact of sharp turns and buildings cutting off the line of sight to the lead vehicle with respect to distance.

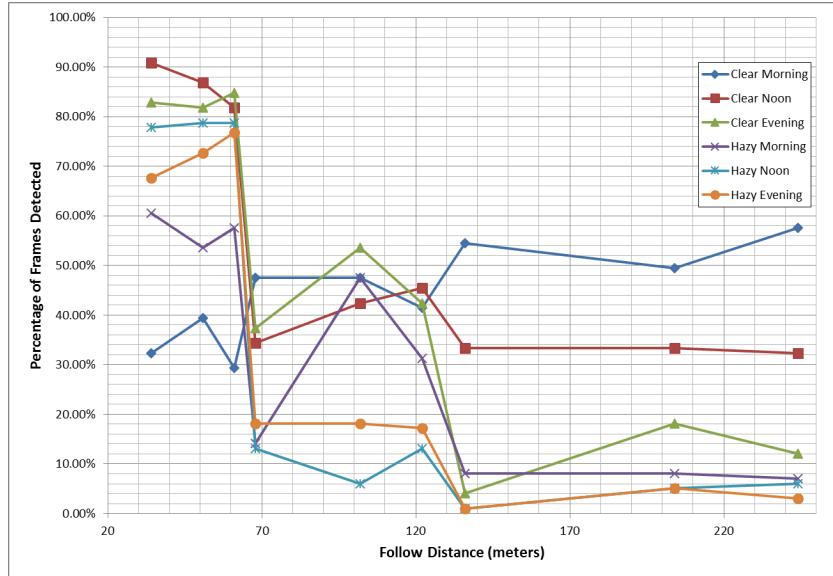


Figure 8. Percentage of frames detected for the Urban scene

The standard error of the mean was taken for all the environmental conditions and all of the terrain conditions and plotted versus following distance in Figure 9. The graph shows that the impact of the terrain conditions lies in the region of approximately 60 meters to 135 meters behind the lead vehicle. At distances before and after this region of space, there is little difference in impact from the various terrain conditions. The graph also displays that the environmental conditions did not have a significant effect on performance and that haze was not a significant performance limiter. The best performance was in the simulated rural and forest areas while the worst performance was in the urban environment. All three terrains, regardless of environmental conditions or time of day, show a steep decrease in performance for following distances greater than 120 meters.

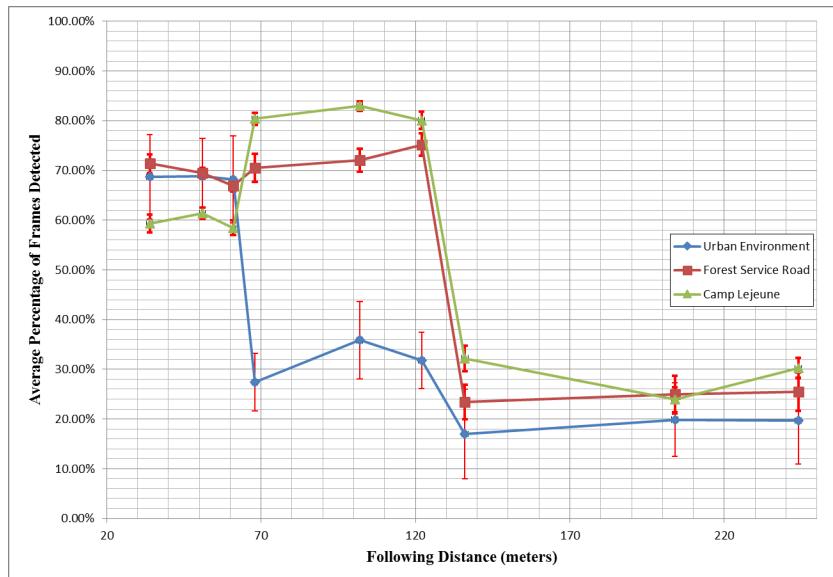


Figure 9. Percentage of frames detected for the Urban, Forest, and Camp Lejeune scenes

5. CONCLUSION

A simulated sensitivity analysis study was conducted using high performance computing (HPC) to determine the environmental effects on object detection in different terrains and environmental conditions. The Virtual Autonomous Navigation Environment (VANE) was used to simulate high-resolution models for environment, terrain, vehicles, and sensors. Three different terrain conditions (rural, urban, and forest), two environmental conditions (clear and hazy), three different times of day (morning, noon, and evening) and six different standoff distances were used to perform the sensor sensitivity analysis. Feature matching was used to detect the markers in each frame of the simulation, and the percentage of frames in which one of the markers was detected was recorded. The standoff distance produced the biggest impact on the performance of the camera system, while the camera system was not sensitive to environmental conditions. Initial sensor performance simulation results show that gap distances greater than 120 meters have a major impact on camera systems. However, simulations that incorporate autonomous algorithms have not yet been performed, and results may change when more advanced autonomy is included.

REFERENCES

- [1] Goodin, C., Kala, R., Carrillo, A., and Liu, L.Y., "Sensor modeling for the virtual autonomous navigation environment," IEEE Sensors, (2009)
- [2] Goodin, C., Durst, P., Gates, B., Cummins, C., and Priddy, J., "High fidelity sensor simulations for the virtual autonomous navigation environment," Simulation Modeling and Programming for Autonomous Robots, (2010)
- [3] Goodin, C., Gates, B., Cummins, C., George, T., Durst, P., and Priddy, J., "High-fidelity physics-based simulation of a UGV reconnaissance mission in a complex urban environment," Proceedings of SPIE, (2011)
- [4] Durst, P., Goodin, C., Song, P., and Du, T., "Route planning for autonomous unmanned ground vehicle operations in urban environments," NDIA GVSETS, (2013)
- [5] Goodin, C., Price, S., Durst, P., Bray, M., and Kala, R., "Vehicle and sensor performance tradeoff study with the virtual autonomous navigation environment," M&S Journal, (2014)
- [6] ERDC, GSL., "Virtual Autonomous Navigation Environment (VANE) User Guide," (2015)
- [7] Goodin, C., George, T., Cummins, C., Durst, P., Gates, B., and McKinley, G., "The virtual autonomous navigation environment: high fidelity simulations of sensor, environment, and terra mechanics for robotics," Proceedings of Earth and Space, (2012)
- [8] Bay, H., Ess, A., Tuytelaars, T., and Good, L., "Speeded-up robust features (SURF)," Elsevier, (2008)
- [9] Khan, N., McCane, B., and Wyvill, G., "SIFT and SURF performance evaluation against various image deformations on benchmark dataset," International Conference on Digital Image Computing, (2011)