



Snow Rendering for Interactive Snowplow Simulation - Supporting Safety in Snowplow Design

Final Report

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16. Abstract (Limit: 250 words) <p>During a snowfall, following a snowplow can be extremely dangerous. This danger comes from the human visual system's inability to accurately perceive the speed and motion of the snowplow, often resulting in rear-end collisions. For this project, the researchers' goal is to use their understanding of how the human visual system processes optical motion under the conditions created by blowing snow to create a simulation framework that could be used to test emergency lighting configurations that reduce rear-end collisions with snowplows. Reaction times for detecting the motion of the snowplow will be measured empirically for a variety of color set-ups on a simulated snowplow that slows down while driving on a virtual road with curves and hills. Current efforts have implemented a blowing snow model that will eventually be integrated into a real-time driving simulation environment. Concurrently, a simulated driving environment has been developed that will serve as the basis for testing the effects of color and lighting alternatives on snowplows. In initial pilot experiments, the simulated driving environment has been effective at testing subject reaction times for following a snowplow through high luminance contrast (normal daylight driving) and low luminance contrast (daylight fog) conditions. The results of this work will move the researchers closer to determining optimal color and lighting configurations on actual snowplows.</p>			
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Executive Summary

When driving during snowing conditions, following a snowplow truck creates an extremely dangerous situation. The danger comes from the human visual system's inability to accurately perceive speed and the motion of the truck, often resulting in rear-end collisions. The overall objective in our research is to use our understanding of how the human visual system processes optical motion under conditions created by fog, blowing snow, or general low visibility to create a simulation framework that can be used to test emergency lighting configurations on snowplow trucks. We feel that such a simulator has the potential to reduce rear-end collisions with snowplow trucks as it could be used to test a variety of dangerous driving scenarios. In our simulation framework, we have conducted a series of experiments to measure reaction times for detecting motion of the snowplow truck. We have performed these experiments to achieve empirical measurements for a variety of warning lighting set-ups on a simulated snowplow that slows down (and speeds up) while driving on a virtual curving, hilly road. This driving simulator environment serves as the basis for testing the effects of alternative lighting configurations on the backs of snowplow trucks. The results of this work will move us closer to determining optimal lighting configurations to make driving under low visibility safer.

During the first two years of this work, supported during the FY 2008 and FY 2009 periods, our primary efforts were on developing a simulation framework capable of rendering visual snow in a real-time simulation environment. The snow rendering system developed during the first two years is capable of rendering a few million snow particles at interactive rates. These snow particles are subject to an average wind field and reflect off of simple geometric structures in the simulation environment. This allows us to move the snow particles during a simulation to mimic the effects of blowing snow in a road-based setting. As part of the efforts during the first two years, we developed a 3D model of a snowplow truck and a 3D roadway to use in future experiments and simulations. The snowplow truck is realistically modeled and has been constructed to easily allow interchangeable back ends with different lighting configurations. While not integrated with the blowing snow simulation system, we also developed a base driving simulation framework that has been used during the third year's experiments. Initial prototypes for experimental design and evaluation were started during year two.

In summary of the first two years' work, our approach is unique and powerful because we compute the effect of snow falling between an observer and the background on a per-snow particle basis. This is an important feature because we achieve critical environmental influences of the snow from this model, such as blurring of elements in the background and a lowering of the contrast between background and foreground elements. The latter is important for addressing the perceptual issues associated with driving in snowy conditions [1-3]. Equally important is the fact that each particle moves under the influence of a physics-based, wind dispersion model. The lighting and motion combine to produce more realistic circumstances. Other research has incorporated spectral methods to represent the effect of falling snow [4]. However, our proposed approach can result in more realistic looking scenes because we explicitly model the falling snow and its effect on the environment. Our approach is also in contrast to methods that treat participating media (fog, haze, or air molecules) as an aggregate [5, 6], deriving functions for how light attenuates across distance rather than dealing with individual particles. Aggregate methods, however, may be important for simulating the influence of snow at distances far from

the observer since our snow rendering framework is somewhat limited by the number of snow particles that can be rendered at real-time rates. We utilize an aggregate rendering for snow at far distances. In our snow-rendering framework, we compute a lighting equation that approximates basic scattering effects for each snow particle. This is feasible due to the computational power and parallel processing available in modern graphics hardware. Current graphics cards, typically used to accelerate video game computations, contain graphics processing units (GPU) that are highly parallel vector processors. Typically, these processors are used strictly for computer graphics rendering equations. However, the literature on graphics hardware programming contains many examples of GPUs being used to accelerate scientific, engineering, and graphics applications. In many of the cases, GPU-based implementations greatly outperform their CPU counterparts, sometimes by several orders of magnitude. This increase in performance relates to the GPU's SIMD (single-instruction, multiple data) style of processing. The lighting calculation applied to each snow particle attempts to characterize the absorption, emission, and scattering of incident light on the snow particle. These components are related to the optical properties of snow. For packed or aggregate snow, researchers have attempted to determine the optical properties for the light-snow interaction [7,8]. The optics of falling snow is different, but few studies applicable to graphics have been conducted to directly determine the optical properties of falling snow [9]. Yonas and Zimmerman [1] have attempted to make some preliminary measurements for light propagation in snowy conditions. Our snow simulation runs at interactive rates performing basic forward scattering from the lights defined in the scene. While we have not yet integrated the snowplow with the snow simulation, we are able to show the effects of the forward scattering in our test scenes.

In the third year of work on this project, we conducted experiments using our driving simulation framework to test rear-end lighting configurations on the backs of snowplow trucks. This report summarizes the driving simulation framework used in the experiments, along with the specific set of experiments used to understand how alternative configurations to the rear-end lighting on snowplow trucks affects motion detection. In particular, our efforts focused on providing lighting solutions that allowed drivers following a snowplow truck in the simulator to detect the approach of a snowplow truck more quickly. Our experiments compared the default lighting configurations under a thick, daylight fog approximation with lighting configurations that attempt to maximize the expansion pattern of the back end of the snowplow truck on the following driver's retina. Our results indicate that by accentuating the truck frame with solid, steady lighting, users, on average, were able to detect the change in motion of the snowplow truck faster than in the standard configuration. We believe these efforts can make driving in low visibility conditions safer, and as a result, we presented this work to MnDOT and Whelen Engineering on December 13, 2011. We continue to work on understanding motion detection in these low visibility situations. For future work, we intend to integrate the snow simulation work from the first two years' efforts into the driving simulation framework to better understand the effects of snowplow truck lighting under varying environmental conditions.

This report concludes this research project. Additional information about the snow simulation system is provided in the FY 2008 and FY 2009 reports.

Chapter 1. Introduction

Our ability to perceive motion in general and optical expansion in particular is crucial for safe driving. Expansion indicates that we are approaching the car ahead of us. In previous work [1,2], two situations were found that interfere directly with our perception of the expansion motion that alerts drivers that collision is imminent: fog and blowing snow combined with the color of the vehicle and the color of the surrounding road can create a dangerous equiluminant situation. In an equiluminant situation the brightness of the vehicle and the background are equal. This can also be described as a low luminance contrast situation since the contrast between foreground and background luminance is minimized. Luminance can be thought of as the amount of light intensity, but not color, that comes from a surface. When equiluminant, or low luminance contrast situations are present, our ability to detect motion is reduced as well as our ability to locate objects in space [3]. In particular, these situations present themselves under snowing or foggy conditions. Also of note, flashing lights, such as those used to improve detection of snowplows in poor visibility conditions, interfere with our ability to sense approach [2]. Our past data indicate that daytime driving behind an amber colored snowplow with amber flashing warning lights strongly reduces our ability to sense approach, increasing the potential for rear-end collisions with snowplows.

The research issue addressed in this report is on investigating how alternative lighting configurations on the back ends of snowplow trucks can improve safety in low visibility driving conditions. Our prior years' work developed a blowing snow visual simulation framework that can be used to investigate how blowing snow (and even foggy) conditions can affect perception of exocentric vehicle speed [3], motion, and general detection. Such a simulator must be capable of providing visual information in real-time based on changing conditions. Our efforts during the first year were on developing the infrastructure to support the rendering of falling snow. The objective of this system is to create equiluminant, or low-luminance contrast conditions, in the visual simulation that can be used to better understand our behavior under these adverse situations. Physical measurements were acquired in previous research to gauge how falling or blowing snow filters the color components of the light that reflects from the painted surfaces of a snowplow [1].

Computer-based psychophysical studies of the effects of luminance contrast and flashing displays on our ability to detect approach were also been previously conducted [2]. The information obtained from these past measurements have prompted and influenced the implementation of our current driving simulation framework and the experiments we conducted to better understand the effects of lighting configuration on aiding the detection of motion under low visibility driving situations. The overall goal of this research tact is to create safer winter driving conditions by applying information about human perception to the design and configuration of snowplow lighting and paint color. To accomplish this, we built a virtual driving simulation environment in which dense fog is rendered and an autonomously controlled snowplow truck drives over simulated 3D roadways. We place subjects in a vehicle that follows the snowplow truck, and they receive visual information on a monitor showing them what they would see if driving the following vehicle. Using the visual, driving simulation system, we can experiment with different snowplow lighting configurations and snowplow paint colors.

Through this virtual prototyping system's results, we expect to be able to provide reasonable input for real-world tests and experiments validating any alternative lighting configurations.

The key components of the research in this project were to (1) develop an effective visual simulation of snow for use in a virtual environment, and (2) begin experimental analysis of how human perception under these circumstances is affected when provided with different lighting configurations on a snowplow truck. The work conducted during the first two years has primarily been to create the snowing simulation effects and is documented in the FY 2008 and FY 2009 reports. The investigation of alternative lighting configurations was primarily conducted after the first two years of work and is documented in this report.

The remainder of the report will highlight the driving simulation framework, the experimental setup, and our experiments investigating alternative lighting configurations on the backs of snowplow trucks. Chapter 2 provides background information for this report and also discusses the mechanisms for autonomous agent simulation used in our driving simulation framework. Chapter 3 details the driving simulation framework system and includes the experiment methodology used to investigate lighting configurations. Chapter 4 present the results from the experiments, and provide guidance for how the project should proceed in future years to provide the most benefit to other researchers in this area.

Chapter 2. Background and Related Work

This work is motivated by the use of virtual environments, such as visual driving simulation frameworks, as a medium for investigating human behavior. Virtual environments present an exciting medium for the study of human behavior that combines the rigor of controlled laboratory experiments with the ecological validity of natural experiments. Virtual environments immerse subjects in worlds that appear physically real, but where conditions can be controlled. Moreover, virtual environments can realistically simulate dangerous circumstances without risking injury to subjects [20, 21, 22, 23].

To exploit the potential of virtual environments as laboratories for psychological experimentation, we must be able to control the dynamics of complex virtual environments populated with vehicles, pedestrians, bicyclists, and traffic lights. In experiments, the right things must happen at the right time and place. In addition, the activity should maintain an appearance of spontaneity; subjects should feel that they have complete freedom of action and that other entities in the environment are behaving normally. Events should be embedded in a natural flow of action and appear to be coincidental.

Our driving simulation framework is founded in reactive behavior modeling for virtual environments. We program autonomous behaviors to query the state and structure of the world and use that information to make decisions that will influence the agent's movements and actions in the virtual world. For instance, a vehicle behavior for tracking a lane on a road may query the road to determine both the speed limit and the curvature at a particular point in the road. The vehicle behavior can then use that information to determine a steering angle and acceleration to keep the vehicle on the lane. Our autonomous snowplow truck is simulated using these techniques.

The goal of our driving simulation framework is to make things happen in environments populated with many autonomous characters. To accomplish this, we use several things: (1) a (soft) real-time simulator architecture that supports autonomous characters and scenario direction, (2) a behavior programming framework, (3) an environment description and representation, and (4) a scenario direction component. We use Hierarchical Concurrent State Machines (HCSM) to model autonomous behavior and the Environment Description Framework to represent the environment roadway.

Our driving simulation virtual environment framework is a (soft) real-time, ground vehicle simulator framework built to support experimentation with autonomous characters and scenario orchestration techniques. Simulation objects represent material entities such as vehicles, traffic lights, or gates. Simulator objects are composed of well-defined computational modules representing important sub-systems for controlling the entity's appearance, decisions, and actions. For instance, a vehicle can have a behavior module to make decisions about how fast to travel and how to drive on a road; a dynamics module that performs vehicle dynamics code to update the position and orientation of the vehicle geometry; and a geometric module that describes the physical aspects of the vehicle, as well as which parts of the vehicle are articulated.



Figure 2.1. A user using a head-mounted display and steering wheel to interact with the visual simulation software.

Human subjects are afforded interaction with the simulation through various instrumented components, such as a joystick steering wheel, mouse, or keyboard. Because of the decoupling between behavior simulation, dynamics simulation, and visual representation of the virtual environment, we are able to present different visual output to users of the simulation system. For instance, in Figure 2.1, a user is viewing the virtual, driving simulation environment through a head-mounted display system. The subject is also using a steering wheel system that was integrated in our simulation framework.



Figure 2.2. Image from the driving simulation system in which a subject is driving behind an autonomous snowplow truck.

The picture in Figure 2.2 is a screen capture from a simulation in which a snowplow truck autonomously drives over a 3D roadway. The view shown is what a user sees in the visual display. Users are presented with visual information that mimics what they might see if they were driving behind a snowplow truck on a real road.

The intended design and functionality of the simulation system used for our experiments in this project is to provide a platform with which we can research and experiment with behavior modeling and scenario control strategies and algorithms for human-in-the-loop, real-time, driving simulation environments.

Our simulation system utilizes a database component capable of modeling complex scenes with detailed terrain and cultural features. The road network portion of the database can be queried by simulator objects to determine information about important environment state, such as where the roads are, where the roads go, which roads connect to which intersections, or what objects are on the roads and in the intersections. The environment database component is described briefly in the next section, but a more thorough description can be found in Willemsen et al. [18].

2.1 Environment Representation

We efficiently model the geometric, topological, and logical information in urban environments in our driving simulation framework. This information is required by programs that code autonomous pedestrian and vehicle behaviors, as well as by scenario control programs that orchestrate behaviors to create predictable experiences for participants.

In the real world, driving is highly regulated; lanes channel traffic into parallel streams, signs posted alongside the road signify important changes to behavior, and lines painted on the surface dictate whether lateral movement is prohibited, or not. Road networks are formed where roads connect to intersections. Entrance into and movement through intersections is regulated by traffic control mechanisms and right of way conventions. Intersections route incoming lanes to outgoing lanes via natural corridors. All in all, movement over roads and intersections in everyday life is controlled by well-defined structures, societal rules, and automated regulation mechanisms to minimize congestion and accidents.

Moreover, as humans, our perceptual apparatus easily sense the nearby objects on the roadways, and we use that information to avoid collisions and unnecessary contact with those objects. We understand the complex relationships between objects on roadways and within intersections.

We encapsulate these environment characteristics into a well-defined and structured environment modeling framework that supports autonomous behavior and scenario programming through a set of run-time queries, structures, and inter-object relationships.

This section briefly describes the *Environment Description Framework* (EDF). The EDF models road networks by defining a road-based representation that supports programming of autonomous agents in real-time virtual environments. As its core function, the EDF gives structure and meaning to physically-based components while overlaying logical and spatial relationship information on the geometric structure of the environment.

The purpose of the EDF is to efficiently model the geometric, topological, and logical information required by programs that code autonomous pedestrian and vehicle behaviors. The EDF database is also used by scenario control programs that orchestrate behaviors to create predictable experiences for participants.

The structures in the EDF are based on the nature and function of real road networks in urban environs. In the real world, driving is highly regulated; lanes channel traffic into parallel streams, signs posted alongside the road signify important changes to our behavior, and lines painted on the surface dictate whether lateral movement is prohibited, or not. Road networks are formed where roads connect to intersections. Real intersections are not free-for-alls; entrance into and movement through intersections is regulated and controlled.

Intersections route incoming lanes to outgoing lanes via natural corridors. As humans, we have exceptional apparatus for perceiving these corridors and understanding the complex relationships that stem from using them. Right of way conventions order movement through intersections. Traffic control mechanisms, such as traffic lights, explicitly control entrance to the intersection, often on a lane-by-lane basis. All in all, movement over roads and intersections in everyday life is controlled by well-defined structures, societal rules, and automated regulation mechanisms to minimize congestion and accidents.

The organization of the EDF is highly influenced by the behaviors used to control autonomous agents. The key to this organization comes from an understanding of what information, in addition to geometry and topology, is needed by the autonomous agents in the environment.

Through this organization, the EDF emphasizes a strong coupling between behavior simulation and environmental structure. In essence, behavioral implications are furnished by the environmental structure to assist autonomous agent decision making processes. The coupling between behavior and environment is central to ecological psychology. J.J. Gibson introduced the idea of environmental affordances for behavior. He asserted that humans perceive much more from the environment than basic sensory information. He argued that the environment provides humans with contextual and relational information [24].

The EDF defines structural, logical, and relational properties in the database components to integrate behavior and environment representations. Structural components provide detailed geometric and topologic information. For instance, roads and intersections represent structural components. The road surface is composed of purely geometric representation forming the so-called pavement of the environment. Intersections have shape and define a boundary. Roads connect to intersections along this boundary creating the road network topology.

Logical attributes describe the culturally important and socially responsible aspects of the urban environment. For the most part, these properties influence the autonomous agents' actions within the confines of the EDF's structural components. Lanes, lane lines, roadside features, intersection corridors, and traffic control mechanisms all represent logical aspects of the EDF.

In the EDF, relational components describe spatial and inter-object adjacency information. In addition, relational components are used to link important behavioral relationships with context-dependent behavior. Occupancy information is calculated by the simulation and stored in the

EDF to spatially locate the autonomous agents with respect to the structural components of the EDF. Adjacency is defined in terms of which objects are in front of, behind, or next to the nearby autonomous agents. Corridor dependencies mark important intersection relationships on a corridor-by-corridor basis.

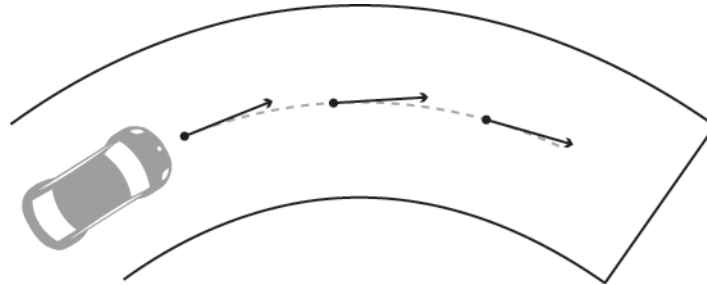


Figure 2.3. A vehicle navigates over a ribbon-like surface inquiring about the tangent and curvature properties at various points along the surface.

Road-like structures can be modeled as ribbons in space. A roadway is naturally expressed in terms of a space curve with surface orientation defined by surface normals. Objects in the simulation environment follow the curvature of the road. Figure 2.3 illustrates a vehicle following the curvature of a ribbon-like surface. Objects avoid collisions by detecting surrounding objects and taking appropriate actions to avoid contact. For instance, vehicles stay within the lanes of roads and slow down to avoid collisions with objects in front of them. Pedestrians dodge and weave around nearby pedestrians on crowded sidewalks.

The driving surface in the EDF is described by a reference curve in 3D space with a surface extending outward, away from the curve. Way points, features, and object positions are all located relative to this surface. Elevation, curvature, tangent, and surface normals are important surface or curve features that are embedded in the surface description. The values of these attributes may change as a function of surface position. For example, curvature at one point on the surface may not be the same as curvature just a small distance away. In general, the information needed by autonomous behaviors is often dependent on structural context and location on the road surface.

Road surfaces in the EDF are represented in curvilinear coordinate systems. Curvilinear coordinates provide a natural means for describing positions and relative locations on the road surface. A curvilinear coordinate system is a two-dimensional coordinate system based on a three-dimensional reference curve that acts as the major axis. The minor axis is defined as the vector perpendicular to the major axis and the surface normal.

The curvilinear coordinate system used in the EDF defines the first dimension as *distance* (δ), and the second dimension as *offset* (o). Distance is measured as the arc-length along the reference curve. Offset is given by the shortest distance to the reference curve as measured linearly along the minor axis. A single curvilinear coordinate is described by the pair (δ , o). Using this system, points on the surface can be uniquely located with both a distance (δ) and an offset (o) parameter.

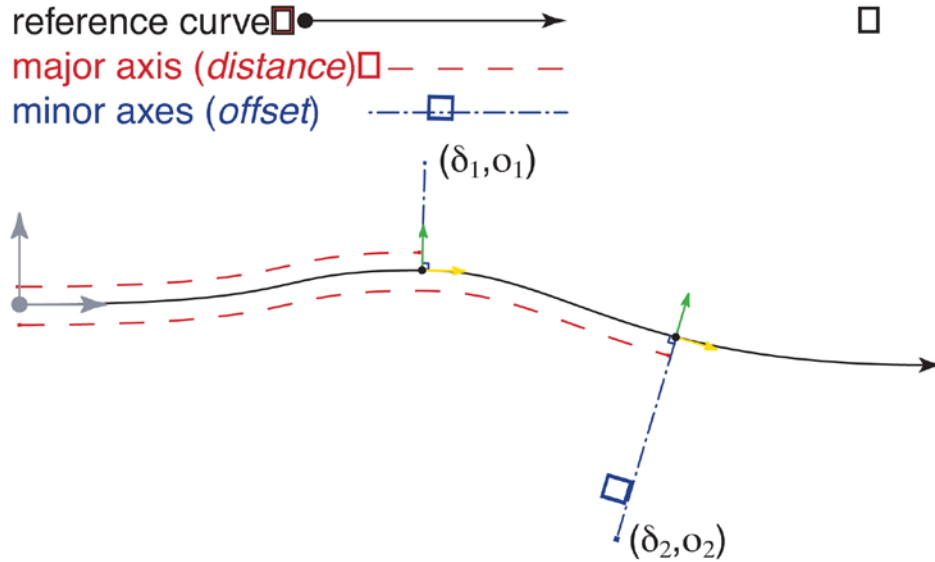


Figure 2.4. Illustration of a curvilinear coordinate system. Two curvilinear coordinates are shown depicting different locations.

Coordinates on a curvilinear surface are defined from an origin, which is defined as the starting location of the reference curve. At this location, both distance and offset are zero. Offsets with positive value are located to the left of the reference curve and offsets with negative value are located to the right (when viewed in the positive direction of the major axis). A curvilinear coordinate frame is illustrated in Figure 2.4. The distance and offset measures define ordering relations for objects on the surface that are the basis for determining spatial relationships of objects on roads in the EDF.

Curvilinear coordinates are used in the EDF database as a basis representation for all navigable routes. Behavioral objects, such as vehicles and pedestrians, track curvilinear coordinates to follow roads, lanes, and routes through intersections. For road-based behaviors, curvilinear coordinates are extremely useful: (1) they naturally represent locations along a road-like surface thus facilitating road and lane tracking behaviors, (2) relative spatial locations are easily defined with respect to the curve which is instrumental for following and obstacle avoidance behaviors, and (3) conversions between curvilinear and Cartesian coordinates afford flexibility in programming autonomous agents as different coordinate systems can be used for different purposes.

In summary, EDF segments provide the foundation for modeling road surfaces. EDF segments are curvilinear coordinate surfaces that analogous to ribbons of pavement through the environment. Segments provide queries for interrogating the surface information and converting between local curvilinear coordinates and Cartesian space. Using hierarchical composition, segments can be combined to form more elaborate pathways that mimic the construction style of roads found in the real world.

As a person drives over the length of a real road, that person's behavior is apt to change and reflect the features and markers posted or painted along the roadway. Some types of markings, such as speed limit zones, affect large expanses of road while others, Bump or Lane Ends signs

for instance, provide more immediate and local information. In the EDF, range attributes describe curvilinear expanses of road in which specific behavioral or societal rules apply. Similarly, the EDF uses features to model localized, situated information that exists at specific distances along the length of the road.

During a simulation, the EDF maintains information about the simulation objects located on each road's surface at any instance of time. This information can be queried providing behaviors with important road occupancy detail. Object location on roads, as well as how those objects' locations relate to each other, facilitates following and obstacle avoidance behaviors.

In the EDF, the term occupancy means how simulation objects occupy space on roads, intersections, and corridors. For our purposes, occupancy is a by-product of an orthographic projection of the objects' geometry onto the ground surface, and hence onto the EDF structures covering the ground. It is quite important that both animate and inanimate objects be included in occupancy computation. For instance, we expect pedestrians walking on the sidewalk to dodge and weave around each other to avoid collisions. Likewise, we expect similar behavior if there are lamp posts or parking meters placed along the sidewalk. At the most primitive level, each object in the simulation is represented by a single point denoting the position of its center of geometry (CoG). This coordinate can be used for assigning point-based occupancy.

Additional information on the EDF can be located in [18]. An example of the EDF file format used for the roadway description in the experiments described in this report is found in Appendix A. A large section of the EDF file is not included in the Appendix to reduce size. The EDF file is available by request and will be posted online.

2.2 Behavior Modeling

Autonomous agents and characters form the heart of an engaging, interactive virtual environment experience. Realistic agent behavior contributes to suspension of disbelief on the subject's behalf and brings the subject into the virtual environment [25].

The autonomous characters and behavior models we create for individual agents are instilled with a basic competence to perform required actions and with the agility to engage in realistic interactions with unpredictable subjects. To accept direction, we program agents with public interfaces through which they can receive messages from directors. For example, a vehicle can be instructed to turn right at the next intersection, to increase its driving speed, or to brake suddenly. The directable behavior system in our simulation software is truly semi-autonomous because it combines a responsiveness to guidance with each behavior's normal autonomous activity.

We model semi-autonomous agents that navigate urban environments, such as motorists, pedestrians, and bicyclists. These behaviors require rich access to environment information and state. For instance, a vehicle needs to know where the road is, how long it is, how the road path changes over its length, and where the road connects to an intersection. Moreover, our behaviors require sufficient knowledge about other agents in the environment. To program following behaviors, our agents need to be able to query the environment to determine if other objects are

on the road ahead of it. The environment model is tightly intertwined with the decision making processes of our autonomous behavior models.

The behaviors of vehicles, pedestrians, and scenario directors in our simulation are modeled with a powerful and flexible mechanism for designing high level, reactive and intentional behavior (HCSM). HCSM stands for Hierarchical Concurrent State Machines (HCSM) [26] and is a programming formalism used to model reactive behavior within a simulation environment. HCSM tightly encapsulates behavior into process-based units called state machines. Each state machine may contain child state machines. The parent is responsible for grouping children according to whether they are concurrent or sequential. Concurrent state machines execute independently and in parallel. In a sequential state machine, only one active state machine is allowed to execute at any given time.

Predicates logically connect sequential state machines and dictate when the transitions between active state machines will be fired. Each state machine may also utilize input and output parameters to serve as ways to pass data in and out of the state machine. A state machine's activity function executes the programmed behavior and may produce output parameters. The parent state machines collect their children's outputs and resolve conflicts between those outputs. Once conflicting outputs have been resolved, the parent sets its own output parameters.

Behavioral directives (*buttons and dials*) can also be specified at the state machine level. HCSM does not enforce how directives are used. It is the responsibility of each parent to forward both input parameters and directives to child state machines. Behavioral control is passed up the hierarchy from leaf state machines to the top-most state machine (the *root*) which, in turn, specifies the final control values for the behavior.

We use HCSM primarily for two purposes. One use is to program the behaviors of objects in our simulation environment. Examples of complete behaviors include human driving, bicycling and pedestrian locomotion [27]. Each of these behaviors can be composed of many lower-level behaviors; lower-level HCSM are generally responsible for a particular component of behavior. For instance, in the vehicle driving behavior, one HCSM is responsible for tracking lanes in the road while another maneuvers the vehicle across an intersection.

Chapter 3. Snowplow Truck Lighting Experiments

Using the driving simulation framework described in Section 2, we have conducted several experiments that build on the initial work of Yonas and Zimmerman to better understand driving in low visibility conditions. Our efforts test the effectiveness of lighting configurations on the backs of snowplow trucks for alerting following drivers to the approach or withdrawal of the snowplow truck. The simulation framework runs in real-time and is separate from the falling snow simulation software discussed in the FY 2008 and FY 2009 reports. As such, our current experiments focus on testing snowplow truck lighting configurations under low-luminance contrast conditions, such as fog.

The initial work by Yonas and Zimmerman [1, 2] presented subjects with a flat, 2D image of a snowplow truck that increased or decreased in size on the screen to simulate approach and withdrawal of the snowplow truck. Their experiments provided a base for the methodology used here to examine how alterations to lighting on the backs of snowplow trucks might lead to changes in how fast drivers could detect the slowing down or speeding up of a snowplow truck in front of them. Our work builds on this prior work, focusing specifically on how lighting configurations might create safer driving situations.

Whereas the initial and prior work used flat, 2D digital imagery scaling to simulate approach and withdrawal, this project's efforts are novel in that we attempt to simulate the natural movement of a snowplow truck over a roadway. Our experiments examine how subjects react to changes in lighting configuration when driving through fog over a geo-typical roadway from Northern Minnesota.

3.1 Experiment Overview

All experiments were conducted in the Elliott Hall laboratory of Albert Yonas on the University of Minnesota main campus. The lab was setup to provide subjects a view of a monitor from an extended distance through a framed aperture made of black foam core board. An overview image of the setup is shown in Figure 3.1. The framed aperture was provided to reduce framing effects of subjects seeing the monitor and its frame and to provide them with the effect of looking out of car window at a vehicle in the foreground. This experimental setup was used for all experiments described in this report.



Figure 3.1. Image from the experimental setup in Elliott Hall.

The setup restricted a subject's view through the small frame shown in Figures 3.2 and 3.3. Viewing the computer monitor through this frame ensured that subjects did not see the surrounding monitor frame, the lab walls, the student running the experiment, or other things in the lab. Subjects sat in a chair at the end of the experiment setup. The chair was raised appropriately so that the subjects could sit comfortably and look through the small frame at the monitor on the other side of the experiment table. Subjects had access to a keyboard during the experiment to enter responses to simulation events via keystrokes.



Figure 3.2. Images from the experimental setup in Elliott Hall.



Figure 3.3. Images from the experimental setup in Elliott Hall.

A Dell XPS workstation with an Intel Core2 Quad CPU running at 2.66GHz with 2GB of memory ran the simulations. The workstation contained a NVIDIA GeForce 9800 GTX graphics card to process the visual simulation. Images from the simulations were presented on a DELL 2407WFP 24" diagonal flat panel display. The display was placed 3.05 meters from the subject. The computer was installed with Ubuntu 9.10, a distribution of the Linux operating system.

The driving simulation code was programmed to maintain visual refresh rates of 60.0Hz. Synchronization to the graphics card refresh was additionally locked to 60.0Hz by setting specific hardware driver environment variables (in this case `GL_SYNC_TO_VBLANK`).

The visual simulation was programmed using custom software developed using the OpenSceneGraph (<http://www.openscenegraph.org>) API. OpenSceneGraph is an open-source 3D graphics Scene Graph that uses OpenGL for hardware accelerated rendering of 3D computer graphics. OpenSceneGraph provides high level functionality for loading 3D model files and rendering those models using OpenGL. Because OpenSceneGraph uses a Scene Graph based spatial data structure, it is able to perform optimizations across the geometry in the scene to improve rendering performance. The snowplow truck and 3D roadway models described in the next section were loaded directly by the OpenSceneGraph code at the start of the simulation.

3.2 Snowplow Model

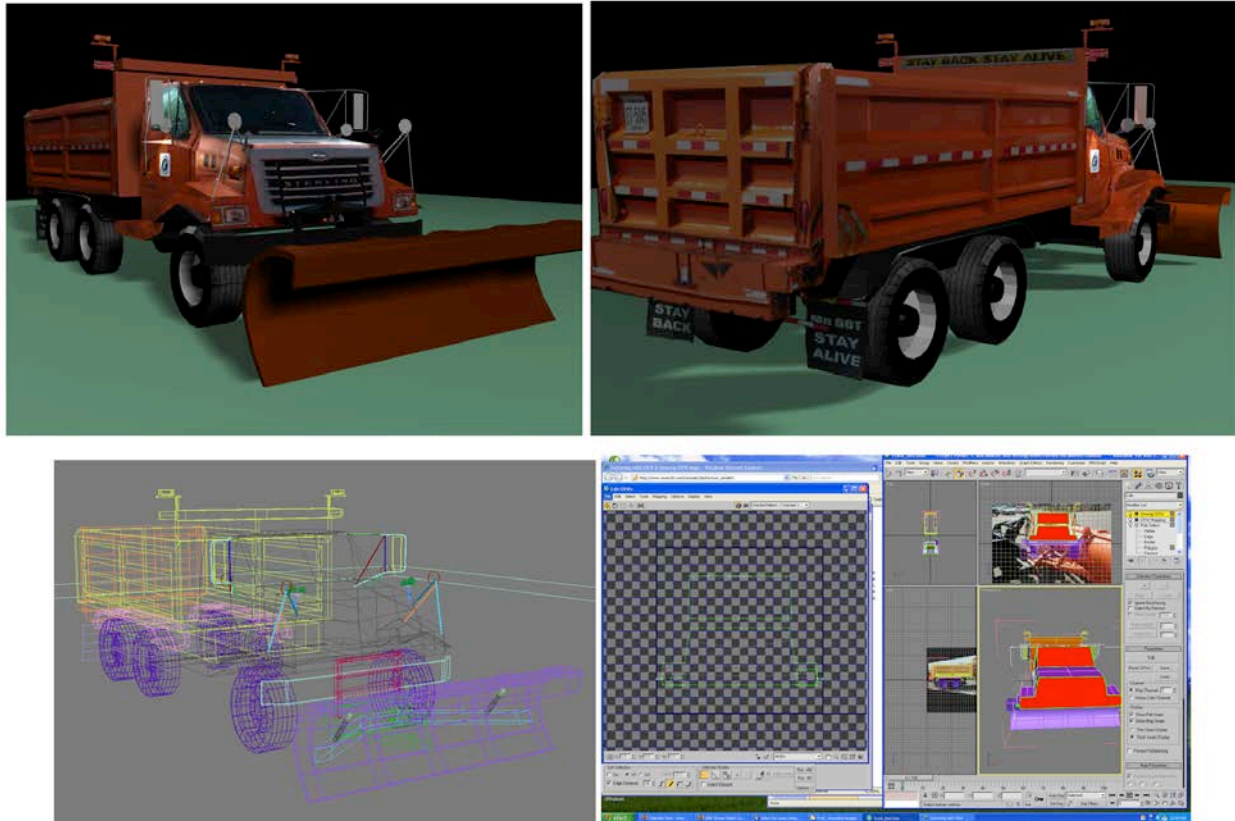


Figure 3.4. 3D Snowplow model. The left panel shows a rendered view of our 3D snowplow model. The wireframe view (right panel) shows the polygons that make up the snowplow model. The current model is a low-polygon model for use in real-time environments. The figure shows two computer-generated images: one of a snowplow and one of the “wireframe” of a snowplow.

A 3-D snowplow truck model was created for use in experiments to validate the snow rendering system and further explore the perceptual effects that result from driving in foggy or snowing conditions. The snowplow model was created with Autodesk’s 3DS Max modeling software. Rick Shomion supplied photographs of MnDOT snowplows and Craig Shankwitz provided information relating to snowplow scale. The snowplow truck model was developed for real-time rendering by (1) optimizing the polygons from which it is constructed, (2) applying suitable material properties for proper illumination, (3) designing a modular back-end so that the rear-end lighting configuration can be swappable, and (4) outfitting the model so that tires rotate and turn based on the vehicle’s motion. Images of the 3D snowplow model are shown in Figure 3.4.

The snowplow truck model was modeled after a standard MnDOT snowplow truck. Images from a typical truck were used to create the model. Several of the images used to create the model are supplied in Figure 3.5. The warning light pattern produced by the lights on the two light stocks was approximated in our simulator software based on observations of snowplow trucks in the city of Duluth, Minnesota.



Figure 3.5. Images used to create the 3D snowplow truck model.

During the course of this project, we conducted several experiments using a range of alternative lighting configurations. In all situations, the simulated 3D snowplow truck model was the same, but was augmented with additional backend lighting. Within the simulation framework, we used dynamic lights on the snowplow and could control whether a light appeared to be on or off depending on the simulation.

These include the lights on the rear of the snowplow, and more importantly, the stroboscopic lights mounted on the top of the snowplow. While we attempted to approximate the stroboscopic effect of a rapidly changing on/off sequence for the light, it is non-trivial to convey the brightness of the lights to a viewer on a LCD screen. The same is true for any lighting fixture on the snowplow truck. The levels of brightness and contrast found in the real world cannot be replicated on current LCD screens, including the screen used in this work's experiments. As such, we attempted to faithfully mimic the light patterns and apparent relative brightness as it applied to our experimental hypothesis and efforts. Future efforts may provide ways in which we can more effectively transmit the brightness of the snowplow's truck lights to a viewer. We expect that techniques like High-Dynamic Rendering or other applied perceptual heuristics could play a role in improving the display of light intensities for experiments.

3.3 Roadway Model

We developed a 3D roadway that consists of approximately 10 kilometers of varying terrain. Figure 3.6 shows the 3D road model used in our real-time driving simulation experiment framework.

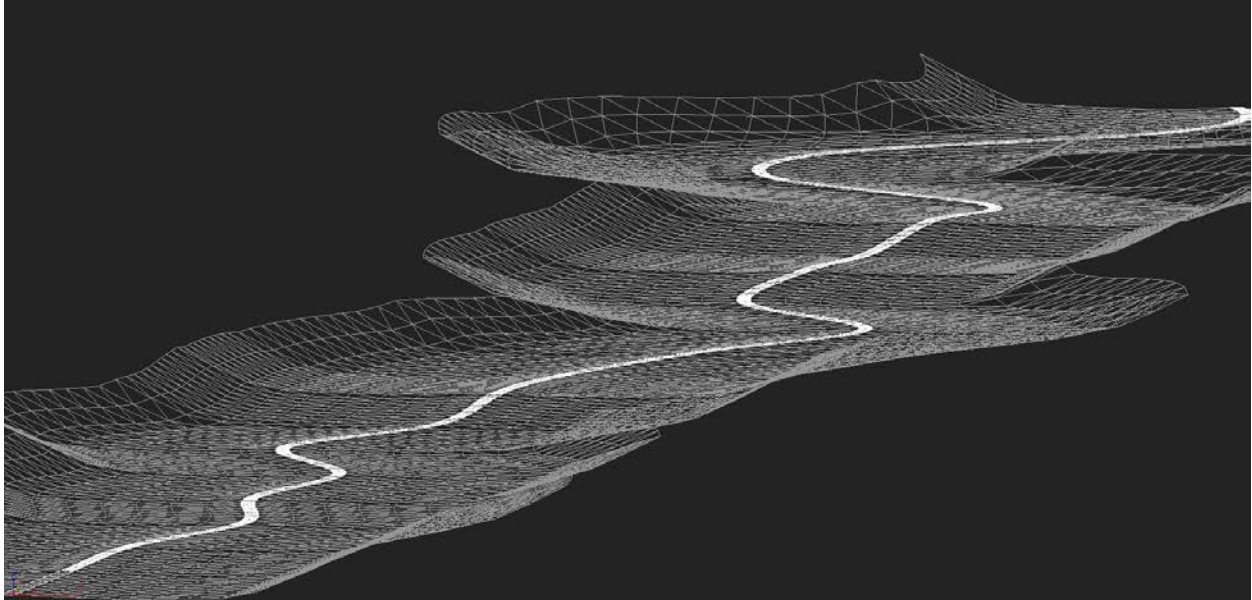


Figure 3.6. 3D Roadway used during lighting configuration experiments. Road direction and height varies across the 10km roadway. The figure is computer-generated.

The 3D roadway was modeled with Autodesk's 3D Studio Max modeling software and was designed to approximate a geo-typical roadway of Northern Minnesota, such as Hwy 53 north of Duluth. The road has elevation changes and curves both to the left and right. The roadway is surrounded by dense pine trees.

The 3D roadway is used in the experiments described below and extends the works of Yonas and Zimmerman by placing the snowplow truck on a plausible road surface. The resulting motion produced by the snowplow truck driving over the surface is more natural and realistic than the scaling of image rectangles used in prior work.

3.4 Experiment Methodology

Our experiment methodology places subjects in a vehicle following the snowplow truck. Subjects are not able to control the speed of the following vehicle, but must react to changes in the snowplow's speed by indicating on the keyboard if the snowplow is approaching or withdrawing from them. The snowplow truck is placed at random locations along the 10km roadway at a fixed speed of 40 miles per hour. After a short random delay, the snowplow either slows down or speeds up with a speed differential of between 5-10 miles per hour speed increase or decrease. We also vary the luminance contrast by providing either high luminance contrast conditions (such as good daylight driving conditions), or low luminance contrast conditions, such as fog.

3.4.1 Experiment 1

In our initial pilot experiments conducted during FY 2009, 2 subjects participated in an experiment to determine if there is a difference between following a simulated snowplow truck under low luminance contrast versus high luminance contrast conditions. Subjects were

instructed to press the 'a' key if the snowplow truck approached them and the 'w' key if the snowplow truck withdrew. Subjects were presented with two luminance contrast conditions representing a clear driving day under fresh snow conditions or a foggy driving day under the same conditions. Luminance contrast was randomized across the experimental trials.



Figure 3.7. Experiments to test the effectiveness of lighting configurations on the back of snowplows are piloted with basic low-luminance contrast versus high-luminance contrast conditions. Normal snowplow lighting is used in both conditions. In the second image, the road and snowplow are partially obscured.

Figure 3.7 illustrates the two conditions. Each subjects was presented with 320 trials each. Subject data is provided below:

- Subject 1:
 - Average High Luminance Contrast Reaction: 2.07s
 - Average Low Luminance Contrast Reaction: 2.44s
- Subject 2:
 - Average High Luminance Contrast Reaction: 1.95s
 - Average Low Luminance Contrast Reaction: 2.66s

What this indicates is that the basic simulator prototype is likely effective at presenting information in which subjects must quickly determine the approach or withdrawal of the snowplow truck. We hypothesized that if the simulator is effective at detecting changes of motion, subjects would be better at detecting these changes under high-luminance contrast conditions and slower to react under low-luminance contrast conditions.

The pilot experiment was followed with an experiment involving four additional subjects. In the follow-up experiment, the trends from the pilot experiment continued.

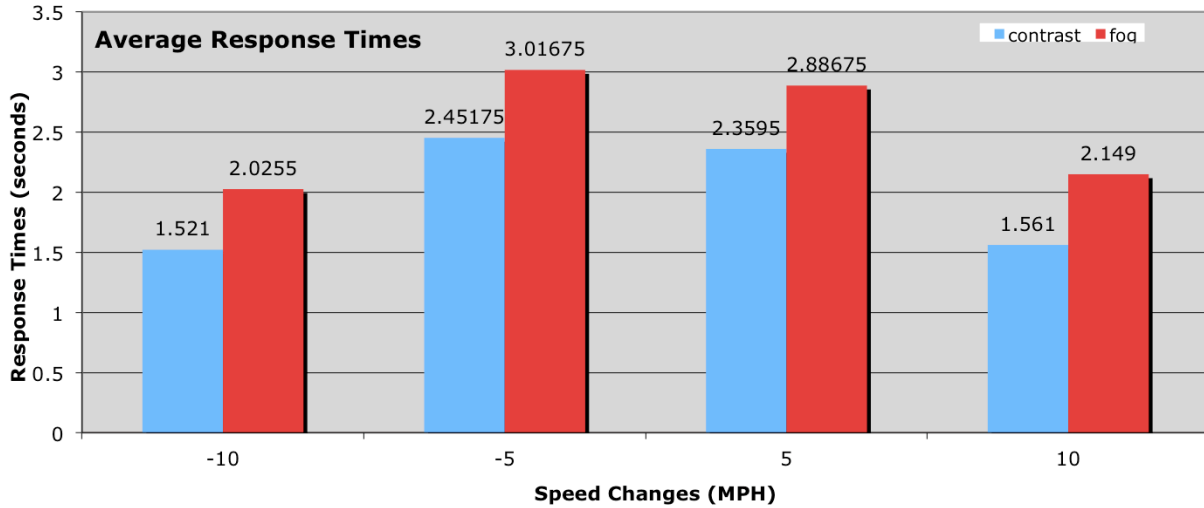


Figure 3.8. Plot of data from Experiment 1 showing average response times in seconds for the high contrast condition as compared to the low contrast foggy condition. Values are plotted for all speed changes.

On average, subjects responded more quickly in the high contrast visual simulation than in the low luminance contrast situations of fog. P values for contrasts between conditions were < 0.05 . Additionally, subjects tended to take longer to detect the approach and withdrawal of the snowplow truck with slower speed changes of 5mph. Figure 3.8 shows the data plot of the average response times for subjects in Experiment 1.

3.4.2 Experiment 2

The second experiment attempted to test the hypothesis that steady burning lights framing the snowplow truck will maximize optical expansion patterns on the retina and result in increased reaction times for detecting approach or withdrawal of the snowplow.



Figure 3.9. Images from the driving simulation showing the different lighting configurations used in Experiment 2. From left to right are the standard snowplow truck lighting, a vertical bar steady lighting, and a vertical bar steady lighting with lighting that adds corners to the vertical bars to frame the back end of the snow plow.

Subjects were instructed to press the 'a' key if the snowplow truck approached them and the 'w' key if the snowplow truck withdrew. Subjects were presented with three lighting configurations illustrated in Figure 3.9. The first condition mimics the standard snowplow truck lighting configuration. The second condition, known as the vertical bar lighting, framed the snowplow truck backend with additional vertical, steady burning lights to frame the snowplow truck bed. The third condition, vertical bars with corners, augmented the lighting from the second condition with horizontal bars to further enhance the bed frame.

Under low-luminance contrast condition of fog, we compared response times for detecting withdrawal and approach of snowplow with the three alternative rear lighting configurations. The experiment was conducted with 19 subjects, each participating in 4 sessions. Each session contained 20 trials.

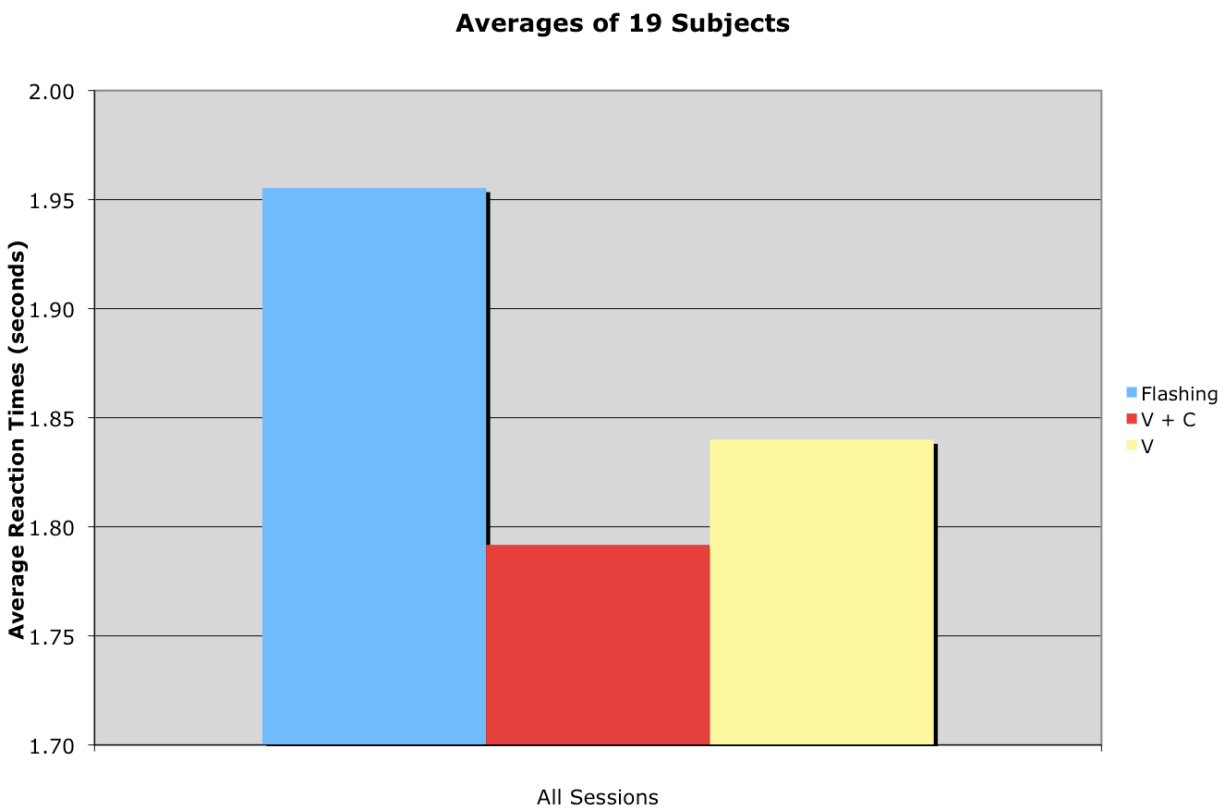


Figure 3.10. Plots of data from Experiment 2. The plot shows the average response time for the standard snowplow lighting configuration with flashing strobe lights, the vertical bar lighting configuration, and the vertical bar with corner lighting configuration.

Average Reaction Times of 19 Subjects

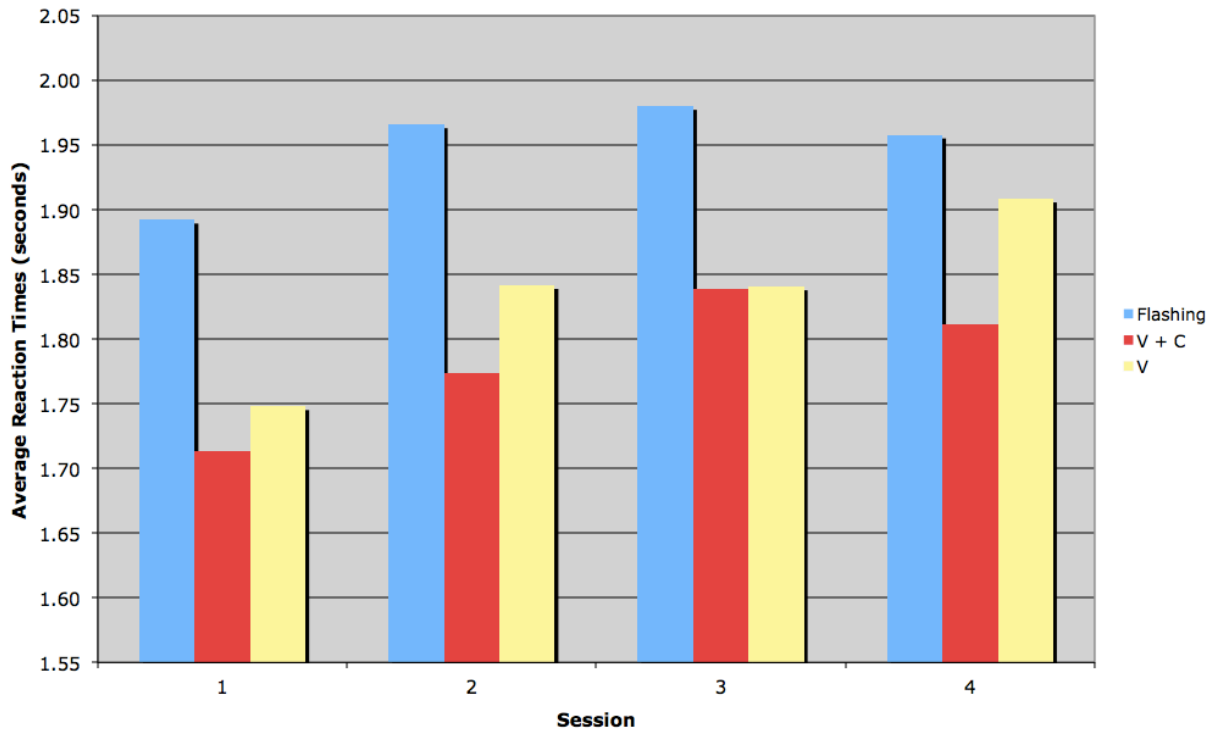


Figure 3.11. Plots of data from Experiment 2. The plot shows the average response time for the standard snowplow lighting configuration with flashing strobe lights, the vertical bar lighting configuration, and the vertical bar with corner lighting configuration. In this plot, average response times from each session are reported.

Figures 3.11 and 3.12 show the data from the second experiment. The average response time for the flashing only condition (the standard lighting model) was 1.96 seconds, while the reaction time for the vertical bar condition was 1.84 seconds. We also found that when the lights on the corners were added to the vertical bars average performance again improved to 1.79 seconds.

The primary result from Experiment 2 is that by adding a steady burning, vertical bar light to the sides of the snowplow truck on the rear panel, it is possible to improve subject reaction time to detecting the approach or withdrawal of a snowplow truck in our driving simulator. While the statistical significance of the difference between the vertical bar lights and the vertical bar lights with corners is not significant, the vertical bar lights with corners did produce a slightly faster reaction time.

3.4.3 Experiment 3

Experiment 3 builds on the results from Experiment 2. We attempt to accentuate the optical expansion information by maximizing contrast of the light signal. Our hypothesis is that by increasing signal contrast of the light configuration, subjects should react faster in detecting the approach or withdrawal of the snowplow truck in the simulator.



Figure 3.12. Images of the snowplow truck lighting configuration from Experiment 3. In the images, from left to right are vertical bar with corners condition repeated from Experiment 2, the vertical bar corner lights with contrast enhancing black edging placed on the interior of the lights, and a circular light configuration with contrast enhanced black bars placed adjacent to the light arrays.

Figure 3.12 shows three low-luminance contrast images from the simulation that depict the vertical bar with corners condition from the second experiment with the high contrast version. A third condition involving circularly placed lights that maximize contrast was also tested in this experiment. However, due to experimenter instruction error during the experiment the data from this condition was removed from analysis. The inclusion of the third condition's image is being included here for completeness. However, we believe that some instructions may have been given to subjects that would have influenced their reactions on the circular condition. We removed the circular data from the analysis and are confident in the results that we did complete.

In the high contrast version of the vertical bar lights, a black bar has been added next to the lights to maximize the contrast of the light signal. In Experiment 3, 21 subjects participated, each viewing a randomized presentation of the three lighting configurations.

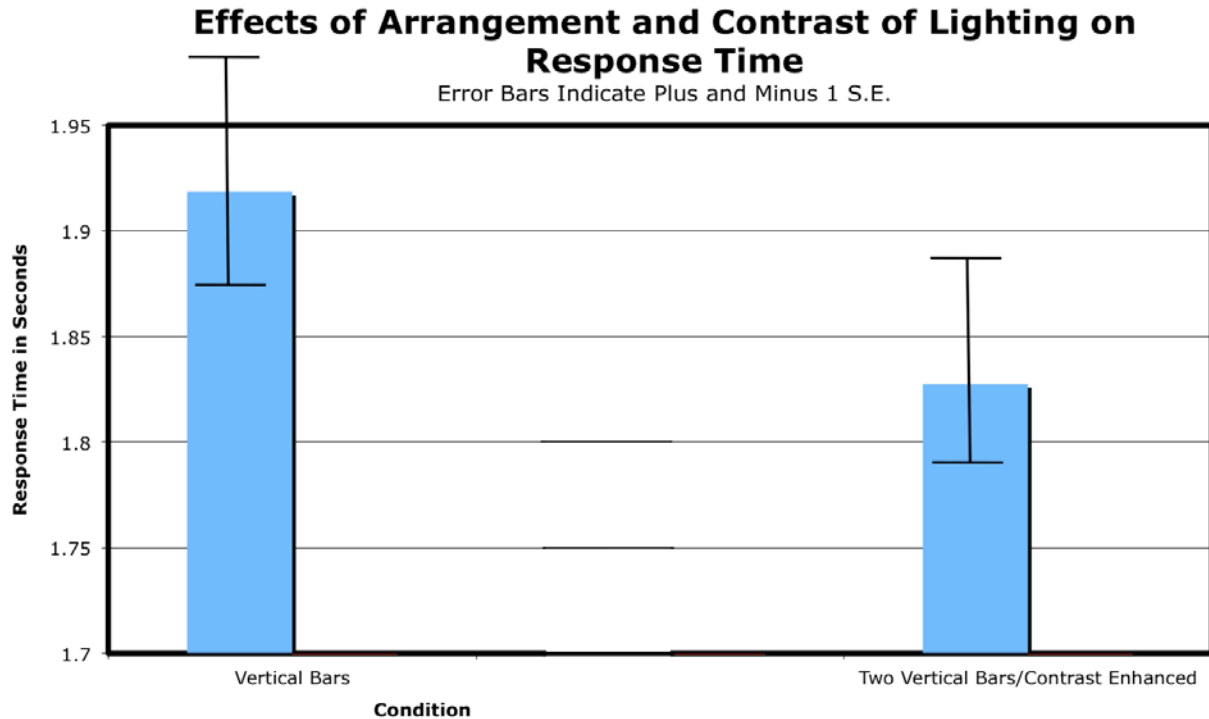


Figure 3.13. Plot of the two analyzed conditions in Experiment 3. The left-most bar chart shows the average response time in seconds of the vertical bars compared with the vertical bars using the contrast enhancing black bars. The contrast enhanced light average response time was statistically, significantly different than the response time from the standard vertical bars arrangement in Experiment 2. The circular light array was not included due to potential experimental error.

Figure 3.13 shows the results from Experiment 3. Subjects reacted faster when lighting was contrast enhanced. Ability to detect information for approach under dense fog or snowing conditions can be substantially improved if lighting on the lead vehicle is altered to optimize the light positioning and orientation. The light patterns in these studies raise the optical expansion information over threshold for subjects in a driving simulation study by increasing contrast. Other lighting designs may be even more effective in improving the safety of drivers.

3.4.4 Experiment 4

The last experiment conducted in this project aimed to further maximize contrast and compare with the standard snowplow truck lighting configuration. Additionally, based on suggestions by MnDOT and other advisors, we focused on a lighting design that has potential to be practical in application on a real snowplow truck. The light bars are meant to be bright LED based constant burning lights placed on the exterior of the snowplow truck bed.



Figure 3.14. Image from the Experiment 4 simulation showing a snowplow truck with rear-end configuration lighting. The lighting configuration attempts to make placement of the light array on the rear of the snowplow more plausible than previous designs. The vertical bar lights are steady burning light arrays flanked by dense black bars to enhance and maximize contrast.

Figure 3.14 illustrates the final design reached by this research project. The primary objective of this lighting configuration design is to increase contrast by surrounding the vertical bright light bars (from Experiment 2) with black bars on either side. This design maximizes expansion information on the retina for impending collision. It improves drivers' detection of approach under low contrast conditions, and lastly, drivers following snowplow respond faster. 29 subjects participated in this experiment. Subjects were instructed to press the 'a' key if the snowplow truck approached them and the 'w' key if the snowplow truck withdrew.

Subjects experienced 3 sessions each. The first session was practice to make sure subjects would perform well. The remaining 2 sessions were analyzed in the data analysis. Subjects experienced 60 trials in each session.

The light strips are steady burning bright LEDs. The black bars adjacent to the lights are meant to be light baffles that increase contrast. Ideally, these black bars would be heated in real conditions to reduce the effect of snow and ice build up on the black contrast enhancing material. We did not research what type of material this needed to be. However, there is precedent for this type of black bar flanking lighter material. On many roadways in Northern Minnesota MnDOT is applying retro-reflective lane marking strips on the highways that have black material flanking the retro-reflective material. This improves and maximizes contrast of the lane marker strip to improve safety while driving. We have applied a similar principle to our LED light arrays on the rear of the snowplow truck in Experiment 4.

Exp 4 - Average Response Time

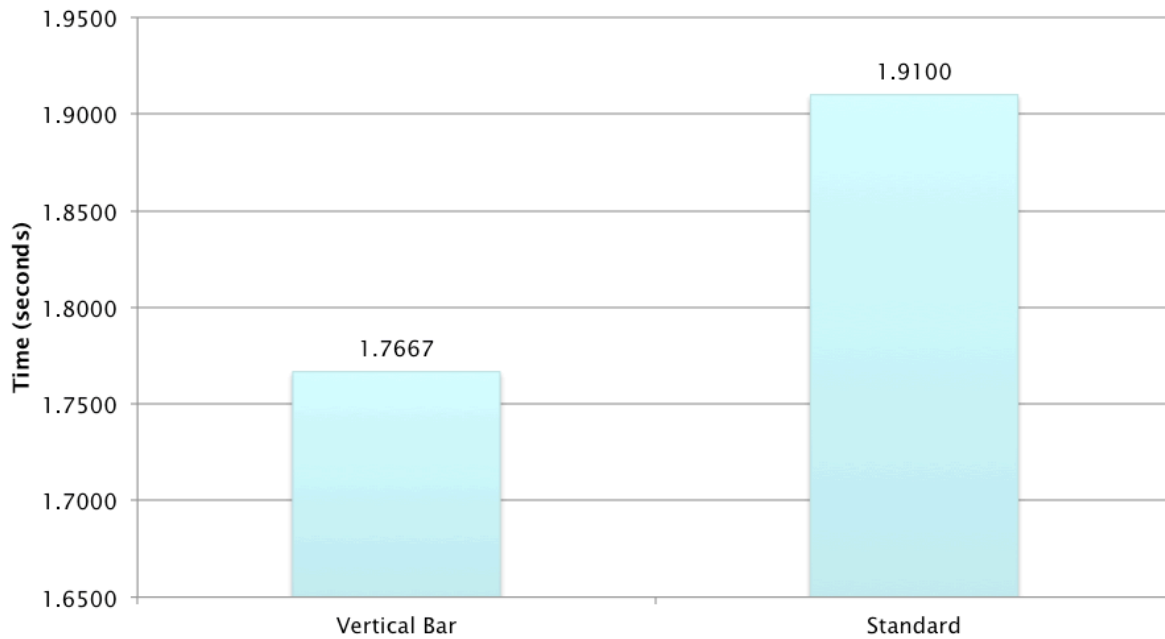


Figure 3.15. Plots from Experiment 4 showing average response time of the vertical bar contrast enhanced light arrays with flanking black bars, as compared with the standard snowplow truck lighting configuration used in our experiments. Subjects performed better on average with a response time of 1.7667 seconds as compared with 1.91 seconds in the control condition. SEM for these averages was 0.0071 and 0.0509 respectively.

On average, subjects performed better in the vertical bar lighting configuration that contained the black bars on either side of the light bar. Standard error of the mean for the Vertical Bar condition was 0.0071 while the standard error of the mean for the standard lighting configuration case was 0.0509. Subjects reliably performed faster at detecting the approach or withdrawal of the snowplow truck in the simulator with this novel lighting configuration. Figure 3.15 illustrates the plot of the data.

In general, we believe this design maximizes expansion information on the retina for impending collision and improves drivers' detection of approach under low contrast conditions. As a result, drivers likely respond faster to the slowing down of the snowplow truck.

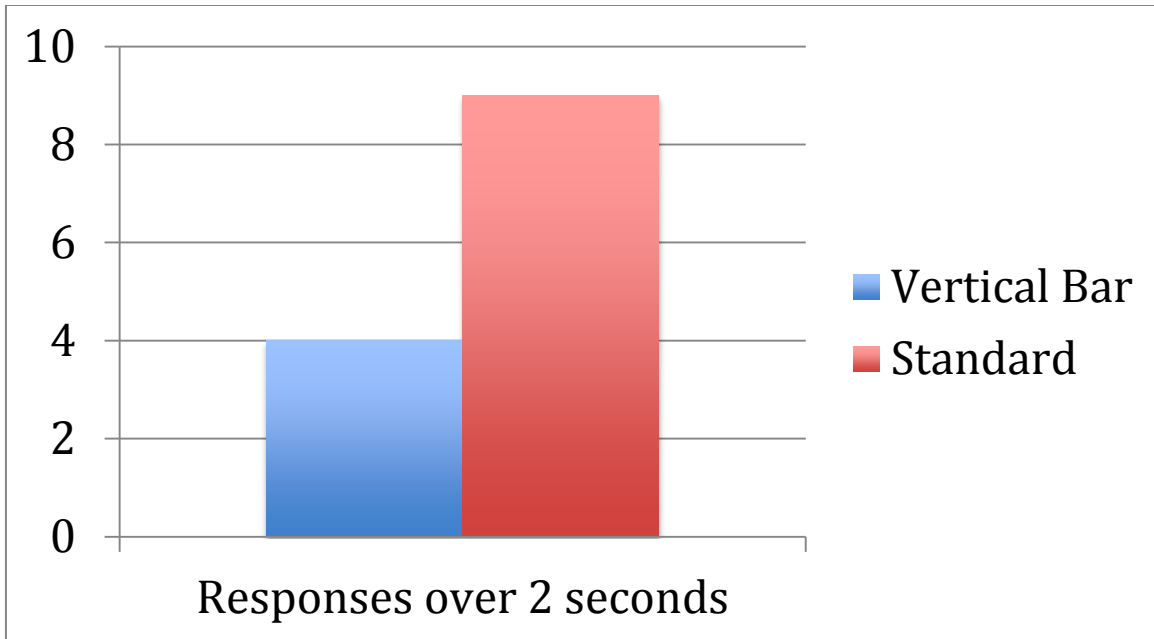


Figure 3.16. Plots from Experiment 4 showing the mean number of responses across the 29 subjects that were greater than 2 seconds. A 2 second response time is considered potentially dangerous. In the plot, the standard lighting configuration average 9 responses greater than 2 seconds as compared with 4 in the vertical bar lighting condition.

We completed additional analysis of the results from Experiment 4. In Figure 3.16, we report the mean number of responses over 2 seconds averaged over the 29 subjects. With the new lighting condition the average number of responses over 2 seconds was half as much as in the standard lighting configuration. This is further indication that providing lighting configurations that maximize contrast and provide visible information that frames the snowplow truck can improve safety in driving, at least within the confines of the driving simulator.

Chapter 4. Conclusions and Recommendations

Low luminance contrast occurring with fog or snow under photopic conditions creates extremely dangerous situations when driving, especially when following other vehicles. In these situations, detecting motion of the lead vehicle is greatly reduced due to low contrast sensitivity. In particular, the expansion information necessary for detecting potential collisions may be poorly integrated. We created a driving simulation framework to test alternative lighting configurations on snowplows to improve detection of approach in low luminance contrast situations, reducing the time to respond in a realistic, driving simulation study. We compared errors and reaction times in a simulated driving task over virtual 3D roadways in which participants judged whether the lead snowplow vehicle was approaching or withdrawing. In our first experiment, we compared lighting that was similar to that used in current snowplows to ones in which vertical non-flashing bars were added to the outer edges of a snowplow and to a condition in which bright corners were added. We found a drop in response time to information for impending collision when non-flashing vertical bars positioned at the left and right sides of the vehicle were added to a baseline display that had only normal flashing lights.

4.1 Conclusions

In general, our experiments have found that increasing the information for optical expansion improves subject performance in the driving simulator. We believe that augmenting snowplow truck lighting arrays with information that frames the snowplow truck will improve safety. Additionally, it is likely that increasing, or maximizing the contrast of the LED light array on the truck will result in drivers seeing the approach or withdrawal of a lead vehicle in a more timely manner. Any decrease in reaction time should help drivers detect the approach of a snowplow truck in a timelier manner and make winter driving safer.



Figure 4.1. Image from the Experiment 4 simulation showing a snowplow truck with rear-end configuration lighting. The lighting configuration attempts to make placement of the light array on the rear of the snowplow more plausible than previous designs. The vertical bar lights are steady burning light arrays flanked by dense black bars to enhance and maximize contrast.

Our experiments focused on how to improve reaction times in a driving simulator. Based on our experiments, we believe that the lighting configuration used in Experiment 4 (Figure 4.1) does the following:

- Maximizes expansion information on the retina for impending collision.
- Improves drivers' detection of approach under low contrast conditions.
- Allows drivers following snowplow trucks in our simulator to respond faster.

These all contribute to making winter driving safer. We have presented this information to both MnDOT and representatives from Whelen Engineering in December 2011. The next stages in this work would be to take our suggestions and results to the test track and test real lighting that satisfies the requirements above. Such efforts would help to understand driver performance in the real world under low visibility situations and work to make driving as safe as possible by maximizing the ties between human perception and the affordances provided by the lights and designs of the structures used on the roadway.

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Appendix A – EDF File for Experiment Roadway


```

units meters
road "snowplow road"
{
  lanedef {
    lane 2 vehicle 4.5 0.0 neg
    axis
    lane 3 vehicle 4.5 0.0 pos
  }
  range_attributes {
    speedlimit (55.0, mph);
  }
  segment spline {
    start_tangent 0.0 1.0 0.0
    end_tangent -0.3658 0.9307 0.0
    points {
      0.2683 -0.9556 0.1090 0.0
      0.2682 15.1734 0.1090 0.0
      0.2682 31.3024 0.1090 0.0
      0.2682 47.4315 0.1090 0.0
      0.2682 63.5605 0.1090 0.0
      0.2682 79.6895 0.1090 0.0
      0.2682 95.8186 0.1090 0.0
      ....
      27.7373 9579.6894 0.1090 0.0
      31.9635 9595.8184 0.1090 0.0
      35.7671 9611.9458 0.1090 0.0
      39.1480 9628.0764 0.1090 0.0
      42.1064 9644.2070 0.1090 0.0
      44.6421 9660.3344 0.1090 0.0
      46.7552 9676.4642 0.1090 0.0
      48.4457 9692.5924 0.1090 0.0
      49.7135 9708.7230 0.1090 0.0
      50.5588 9724.8512 0.1090 0.0
      50.9814 9740.9794 0.1090 0.0
      50.9814 9757.1092 0.1090 0.0
      50.5588 9773.2382 0.1090 0.0
      49.7135 9789.3672 0.1090 0.0
      48.4457 9805.4970 0.1090 0.0
      46.7552 9821.6244 0.1090 0.0
      44.6421 9837.7542 0.1090 0.0
      42.1063 9853.8832 0.1090 0.0
      39.1480 9870.0114 0.1090 0.0
      35.7670 9886.1404 0.1090 0.0
      31.9635 9902.2702 0.1090 0.0
      27.7373 9918.3992 0.1090 0.0
      23.0884 9934.5282 0.1090 0.0
      18.0170 9950.6572 0.1090 0.0
      12.5229 9966.7870 0.1090 0.0
      6.6063 9982.9160 0.1090 0.0
      0.2669 9999.0450 0.1090 0.0
    }
  }
  num_segments 80
}
}

```