Development of a Microscopic
Artificially Intelligent Traffic Model for Simulation

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ABSTRACT

Roadway safety continues to be a major public health concern. Recent statistics show that more than 30,000 fatalities occur due to motor vehicle accidents, and in the year 2012, motor vehicle crashes resulted in more than 2 million injuries. As a result of these ongoing trends, simulators continue to become more abundant in applications ranging from Intelligent Transportation Systems (ITS) research, autonomous driving, human factors studies, rehabilitation, and driver training and workload applications. However, many current simulators lack realism with regards to accompanying traffic, which often does not satisfactorily respond to the real-time actions of the human subject who is operating the simulation. Artificial traffic simulation models found within many modern-day driving simulators are often "macroscopic" in nature – they aggregate the description of overall traffic flow, which is based on "idealistic" driver behavior. This lack of network realism (particularly in the vicinity of the human subject operating the simulator) limits the application scope.

In this paper, we evaluate traffic simulation models for supporting next-generation ITS research applications. This survey justified the need for the design and development of a microscopic Artificially Intelligent Traffic Model (AITM) intended for civilian ground vehicle research applications. The AITM generates a fleet of semi-intelligent vehicles with which a human driver interacts within a virtual driving simulation environment. The behavior of the vehicles is based upon the basic principles of rigid body physics and real-time collision detection, and includes a rule-base for: road-appropriate travel speed behavior, behavior at intersections (e.g., stop signs, street lights), and interactions with other AI and human-driven vehicles on the virtual roads (i.e., lane changing, headway distance). In this paper, the design and development of the baseline AITM is described, and a use-case application is presented, along with recommendations for improvements required subsequent to the deployment of the preliminary model.

ABOUT THE AUTHORS

Viral Raghuwanshi received his M.S. in Mechanical and Aerospace Engineering at the University at Buffalo in 2011, and served as a graduate research assistant at NYSCEDII for almost 2 years. Currently, he is a Software Development Engineer at PartMaker, Inc.

Sarthak Salunke received his M.S. in Mechanical and Aerospace Engineering at the University at Buffalo in 2013, and served as a graduate research assistant at NYSCEDII for almost 2 years. His technical skillsets include a specialty in Virtual Reality, with experience in Programming, CAD, and 3-D software and modeling.

Yunfei Hou is a Ph.D. candidate in the Department of Computer Science and Engineering at the University at Buffalo. His current areas of research interest include the design of cloud-based educational platforms for mobile-end applications (iPad, Android phone and Android tablet), and the development of cyber technologies, for transportation engineering by considering human factors (i.e., the perceptions of the human driver).

Kevin F. Hulme is the technical lead of the Motion Simulation Laboratory at the New York State Center for Engineering Design and Industrial Innovation (NYSCEDII), and focuses on the custom design and development of ground vehicle simulations for applications in: clinical research, education and training, and next-generation transportation studies. Recent areas of focus include: standardization of simulators in teen driver safety, fidelity requirements in simulation system specification, and multi-participant civilian driving simulators.

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INTRODUCTION

Roadway safety is a major public health concern in North America and abroad. Accidents/unintentional injuries are the fifth highest cause of death among all age groups (Murphy et al., 2013). Recent statistics show that more than 30,000 fatalities occur annually due to motor vehicle accidents in the United States (NHTSA, 2014), and there were more than 5 million police-reported crashes (U.S. Census Bureau, 2012). Motor vehicle crashes are the LEADING CAUSE OF DEATH for U.S. teens, accounting for more than one in three deaths in this age group. Furthermore, "unintentional injuries" are the leading cause of death for all age groups up to age 45 (CDC, 2012).

In recent efforts to increase driver training, driver skill, and roadway safety in general, the transportation research simulation community uses two distinct simulator types, often with each operating separately. Traffic Simulation models simulate the movement of individual driver-vehicle units based on car-following and lane-changing theories, and have typically been used for evaluating the system-wide performance of transportation networks (TRB, 2000). Driving Simulation is typically employed for the direct testing of individual human subjects within a virtual environment. Particularly over the last decade, such implementations are used for a variety of research, transportation, safety, clinical, and training applications (e.g., Underwood et al., 2011; Chan et al., 2010). Each simulator model type, when implemented separately, has its own limitations. While traffic simulation models allow for capturing dynamics of full-scale traffic networks, they lack behavioral realism, since vehicle movements are based on human factor theories that are often simplifications of reality. This limits the application of traffic simulation models to the analysis of the transportation system mainly from an operational efficiency standpoint. Alternatively, driving simulation often lacks authenticity and realism. In a majority of driving simulators, for example, accompanying traffic is pre-programmed and does not react according to the real-time actions of the human subject who is operating the simulation. This lack of network realism limits their application to a small subset of vehicle scenarios (e.g. a single roadway intersection) versus larger, transportation system-level evaluations.

This paper describes the design and development of a microscopic Artificially Intelligent Traffic Model (AITM) intended for civilian ground vehicle research applications. The AITM generates a fleet of semi-intelligent vehicles with which a human driver interacts within a virtual driving simulation environment. The behavior of the vehicles is based upon the basic principles of rigid body physics and real-time collision detection, and includes a rule-base for: road-appropriate travel speed behavior, behavior at intersections (e.g., stop signs, street lights), and interactions with other AI and human-driven vehicles on the virtual roads (i.e., lane changing, headway distance). The next section presents a brief survey of existing traffic simulation software, and justifies the need for the present work.

LITERATURE REVIEW

The ongoing growth of urban automobile traffic has led to serious traffic congestion in most cities. Since travel demand increases at a rate that is often greater than evolving road capacity, this situation will continue to deteriorate unless dramatically improved traffic management strategies are implemented. Fortunately, recent advances have enabled Modeling and Simulation as increasingly important tools for traffic control and future transportation networks. Simulation is required not only as a planning tool - to assess the benefits of proposed next-generation transportation systems, but also to generate scenarios, optimize control, and predict network behavior from an operational standpoint. They can provide scientists and researchers with an overall picture of a hypothetical traffic system, and provide the capability to assess current problems (and propose candidate solutions) efficiently. Most

often in transportation research, standalone simulators are implemented to analyze research questions pertaining to planning, operations, logistics, human factors, and safety. These include Driving Simulators (DS), which are typically employed to monitor driver behavior, performance, and attention. Alternatively, Traffic Simulators (TS) are used to better help plan, design and operate transportation systems. Typical traffic simulation models can be classified as either microscopic, mesoscopic, or macroscopic. **Microscopic models** predict the state of individual vehicles; typical measures are individual vehicle speeds and locations. **Macroscopic models** aggregate the description of traffic flow into a "bigger picture", and often employ speed, flow and density as measures. **Mesoscopic models** have aspects of both macro- and microscopic models. (Boxill and Yu, 2000).

Each simulator type, when used independently, has its own set of limitations. A typical DS allows for the analysis of driver behavior by immersing human subjects within a virtual simulation environment and monitoring their reactions. Unfortunately, a DS often lacks traffic authenticity and transportation network realism. In the majority of simulators, accompanying traffic is pre-programmed, and does not respond according to the real-time actions of the human subject who is operating the human-driven vehicle. While TS models allow for capturing the dynamics of large-scale (macro) traffic networks, they often lack driver behavioral (micro) realism where vehicle movements are often simplifications of reality. For the above-stated reasons, various researchers have attempted to integrate these two simulator types. A few examples of recent attempts include a framework (That and Casas, 2011) that combines a commercial traffic simulator (Aimsun) and driving simulator (SCANeR). Another recent effort (Nakasone et al., 2011) introduced OpenEnergySim: a multi-user driving simulator that is capable of integrating with a traffic simulator (X-Roads) using the OpenScience framework. Around the same time, the Utah Traffic Laboratory Driving Simulator (Martin et al., 2012) was designed to integrate VISSIM with a low-cost Driving Simulator (ARCHER). Lastly, (Gomes et al., 2011) developed a coupling architecture between the traffic simulator DIVERT and an in-house Driving Simulator.

Related research has noted that existing microscopic traffic simulation models (based on available car-following, gap-acceptance, and lane-changing models) often lack the level-of-detail required for safety evaluations, which demand models that reflect errors in drivers' perception, decision-making, and actions (Cunto and Saccomanno, 2006). Other researchers (e.g., Punzo and Ciuffo, 2011) have emphasized the four main requirements for appropriately integrated (TS-DS) simulation models. These are:

(1) Accurate road matching between traffic and driving simulators;
(2) Synchronization of traffic and driving modules with real time;
(3) Consistency of the updating calculation frequency; and
(4) Management of autonomous vehicle visualization.

In particular response to these four stated research needs, and to the various shortcomings of the related work that came before ours, we have constructed our own Artificially Intelligent Transportation Model (AITM) intended for clinical, training, and research simulation applications. In this paper, we describe the design of the major components of the AITM, and some of its preliminary shortcomings that necessitated critical modifications. Prior to that discussion, we first present ideas for the extensibility of our work to related domains in M&S research.

BROADER IMPACTS

Ultimately, the microscopic traffic model described in this paper helps to broaden the range of applications for which standalone driving/traffic simulators are applicable. For example, the proposed integration of technologies can be used for these (and other) applications relevant to transportation safety, and public health in general:

Clinical and Human Factors studies in Vehicle Simulation. Historically, driving simulators have been used for targeted interventions for "vulnerable" sectors of our population (e.g., training inexperienced teenage drivers (Hulme et al., 2012), evaluating older drivers with cognitive impairment (Hulme and Thorpe, 2013), treating drivers with Post-Traumatic Stress Disorder (PTSD), and drivers with Attention Deficit and Hyperactivity Disorder (ADHD). As a result, a better "validated" driving simulator with integrated, realistic artificially intelligent traffic (that reflects driver behavior that is based upon factual driver input) could greatly improve the authenticity and overall quality of the driving environment for this sector of simulation-based applications.

Analysis of "Green" Studies in Transportation Science. With a reliable integrated simulation capacity, researchers could more accurately study the anticipated impacts of driving on "green" (environmental) concerns, such as estimated vehicle mileage efficiency and predicted tailpipe emissions (Hulme et al, 2010). This will become increasingly relevant with evolving technologies such as hybrid and electric vehicles, and particularly autonomous driving (Hou et al., 2014).

Future Transportation Planning. Next-generation transportation environments may be capable of communicating with other vehicles and with the traffic infrastructure, and sending warning messages to drivers (e.g., DOT, 2011). Accordingly, an authentic simulation environment is going to be required to examine and fine-tune such a protocol, especially with complex Human Factors concerns (e.g., when to relinquish control to/from a live human driver in a partially autonomous vehicle) that will be involved for a successful implementation of these technologies.

Military Applications: Autonomous Warfare. The technology described in this paper is geared towards applications in civilian ground-vehicle applications, but is certainly not limited to this scope. As military warfare becomes more sophisticated, and more complicated by "improvised" explosive devices on the battlefield, the need for advanced simulation technologies for tactical strategies continues to heighten. Recent advances in autonomous mobility systems could benefit from aspects of the current research. Such emerging technology enables convoy vehicles to traverse dense urban terrain, and navigate hazards and obstacles including pedestrians, oncoming traffic, and road intersections (McDuffee, 2014).

Figure 1 – Driving Simulator (exterior)	**Figure 2 – Driving Simulator (interior)**	**Figure 3 – Virtual Driving Environment**

SIMULATION HARDWARE

The driving simulator utilized in the current research study consists of a six degree-of-freedom electrically actuated motion platform. As seen in Figures 1 and 2, two passengers are accommodated in a front-seat vehicle passenger cabin. The driver supplies inputs to the simulator using a steering wheel (force feedback, with a 900˚ rotational stroke), three pressure modulated/adjustable floor pedals (gas, brake, and clutch), and a console gear-shifter with programmable buttons. Additional simulation hardware includes an Emergency-STOP switch, a four-screen (Front, Left, Right, and Rear-view, hexagonally arranged), front-projected XVGA+ visualization system (4:3, 8' × 6', 1400×1050 pixel resolution), and a 2.1 channel stereo sound system.

ENVIRONMENT DESCRIPTION

The scene graphics for the driver training environment have been developed in-house, rendered using OpenGL, a 3-D C++ graphics API. The primary training environment is a four square mile region that is adjacent to the University at Buffalo. Refer to Figure 3 for a sample user point-of-view screen capture. The environment includes residential streets, 2-lane roads, 4-lane roads, and a 1-mile segment of the New York State Thruway. This training environment is useful in that it allows the participant to practice basic safe driving (e.g., speed maintenance, lane positioning, traffic sign and signal management) within the confines of a controlled and measurable environment. Added to this environment are a number of special hazard scenarios. For example, a road segment was augmented to include roadway cones along both sides, which includes the narrowing of the lanes from two wide-lanes down to a single narrow lane. Another hazard incorporates speed bumps to regulate travel speed (from 35 mph down to 10 mph) along a residential road. Common to Western New York on actual roads, we have also devised a "bad weather" scenario along a segment of the highway, which contains falling/blowing snow, wind effects, and a slippery roadway surface. This forces the driver to minimize heading control (and harsh steering) movements.

With regards to the traffic required to populate this driving environment, as outlined in the Literature Review, many existing microscopic traffic simulation models have shortcomings (level-of-detail, model inaccuracies, lack of synchronization between TS-DS, and others). For these reasons, we have devised our own Artificially Intelligent Traffic Model (AITM), intended for application-oriented driving simulation research applications, whose preliminary design and development is described in the next section.

AITM DESIGN (PRELIMINARY)

In this section, the primary features of the AITM are described, including the motion model (both for linear motion and for turning motion), collision detection between moving objects (both between AI vehicles, and the human-driven participant), models describing vehicle behavior both at signalized intersections and at stop signs, the AI vehicle lane-changing model. This section concludes with an overview of major shortcomings of the preliminary model that necessitated further development.

Linear and Radial Motion

To allow the AI vehicles to navigate within the virtual environment, a function was designed to dictate their basic motion path. For this purpose, equations of motion were implemented based on physics. The motion of the AI vehicles was decomposed into three broad phases: acceleration, deceleration, and turning. The equations of motion are summarized in Tables 1 and 2.

Table 1 – Linear Motion Equations	Table 2 – Radial Motion Equations
$v = s / t$ $v = v_0 + at$ $s = v_0 t + 1/2\, at^2$ $v^2 = v_0^2 + 2as$ where: • v = velocity (ft/s) • s = linear displacement (ft) • t = time (s) • v_0 = initial linear velocity (ft/s) • a = acceleration (ft/s^2)	$\omega = \theta / t$ $\omega = \omega_o + \alpha t$; $\omega = (\omega_o^2 + 2\,\alpha\,\theta)^{1/2}$ $\theta = \omega_o t + 1/2\,\alpha\,t^2$ $\alpha = d\omega / dt = d^2\theta / dt^2$ where: • ω = angular velocity (rad/s) • θ = angular displacement (rad) • t = time (s) • ω_o = angular velocity at time zero (rad/s) • α = angular acceleration (rad/s^2)

The equations in Table 1 account for the acceleration and deceleration motions of the AI vehicles on a straight road. Each time slice was set to the current frame rate of the simulation, which was approximately 60 Hz. Maximum travel speeds are calculated dynamically, based largely on the posted speed limit on each road of travel. Reasonable values for acceleration and deceleration are computed based upon published data for the typical rates at which vehicles speed up and slow down. Stochastic effects were added to the model behavior (e.g., maximum speed, acceleration rates) to add realism, and to assure that all vehicles do not behave exactly the same. Updated vehicle position coordinates are computed based on the heading angle of each AI vehicle, which is assigned in accordance with the global geometry of the road on which it is travelling. Regarding turning (radial) motion, outlined in Table 2, semi-circular arcs were employed between the end-points of the lane centers of two adjacent roads. This way, AI vehicular motion along the turn would be fluent, and angular motion equations were used to approximate the motion of the vehicle while traversing the arc segment. The radius of the arc was identified by using the distance between the end points of adjacent road segments, and the interior angle between the two roads.

Collision Detection

Determining if any two 3D objects intersect – a technique commonly known as *collision detection* - is not an easy task. The key to optimize these calculations is to efficiently discard non-colliding objects before applying a full collision test (to all other candidate objects in the scene). The typical path for discarding objects is to first divide a virtual scene into segments, while keeping track of which segment the object in question is located, and then using collision tests with all the non-discarded objects in that segment. One common procedure is known as the *Oriented Bounding Box* (Eberly, 2008). This method rotates the bounding box with the geometry so that the bounding box represents the geometry of the object, even when rotated. This technique was chosen for the current effort, as the AI vehicles traverse within specific lanes of traffic which are at different orientations, and collision will be detected with other vehicles within the same lane (or adjacent, parallel lanes of travel). Also, a bounding box serves as a

sufficiently accurate representation of the shape of a motor vehicle. As shown in Figure 4, the bounding box is attached to the AI vehicle, and new coordinates are calculated (using matrix transformations) each time the AI vehicle moves or rotates. In addition, the bounding box was extended in the direction of the heading of each AI vehicle to detect collisions with other moving vehicles. The length of the bounding box was assigned to be dependent on both travel speed and the posted speed limit.
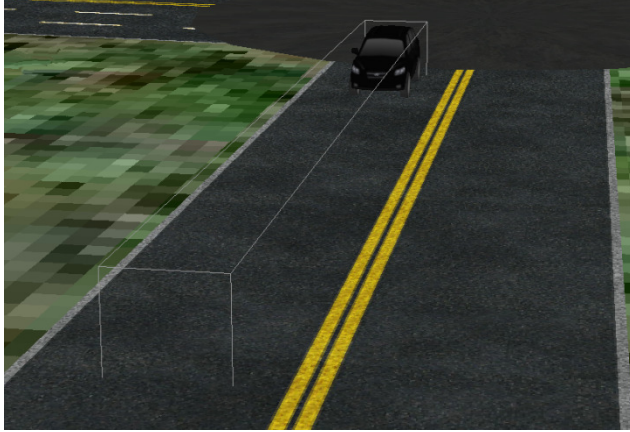

| **Figure 4 – Oriented Bounding Box (3D)** | **Figure 5 – Four-point collision square (2D)** |

The next step was to identify a method that would detect whether or not there is a collision with the bounding box with other moving objects in the scene (and determined to be in the vicinity). The chosen algorithm needs to calculate the distances of all the vehicles within the AI vehicle collision box, and selects the vehicle that is nearest to the AI vehicle. The chosen algorithm then makes collision avoidance decisions based on the position and speed of the nearest vehicle. In this research effort, a four-point collision detection method was implemented. Instead of checking whether a single coordinate point (e.g., the centroid of another vehicle) is within the collision box, the algorithm checks for four points which better resemble the geometry (perimeter) of the vehicle. A sample AI vehicle (and its collision square) can be seen in Figure 5.

After being able to detect other vehicles within the bounding box, we next developed an algorithm which would account for the response motion of the AI vehicles when a collision is detected, to avoid physical contact with another virtual entity. The algorithm calculates the distance between each AI vehicle and its nearest neighbor, and the difference in velocity between the two vehicles. Based on this information, the algorithm calculates deceleration required for the AI vehicle to stop at a safe rate, and within a "safe distance" from the vehicle with which it is detecting collision. The algorithm was designed to accommodate the motion of AI vehicles during all three phases of its motion: Acceleration/Coasting, Deceleration, and Turning, each briefly outlined here:

- **Acceleration/Coasting**: During the acceleration/coasting phase, braking is required to slow down or stop the vehicle if so required (i.e., if a pending collision is detected). After the collision-detected vehicle moves outside of the scope of the collision box of the AI vehicle, the AI vehicle resumes its original motion and gains speed until it achieves the posted speed limit of the road (i.e., coasting speed).
- **Deceleration**: During the deceleration phase, the AI vehicle is already slowing down to stop; perhaps at an approaching intersection. If during this phase the AI vehicle detects collision, a decision is made as to whether to slow down (at a greater rate) to avoid physical contact. If the AI vehicle detects collision and comes to a complete stop, the algorithm resumes the original motion of the AI vehicle when the colliding vehicle is outside of scope (i.e., when it adjusts its motion accordingly enough so that collision is no longer detected).
- **Turning**: During the turn phase, the size of the collision box is intentionally reduced in order to avoid "false" collision detection with vehicles in adjacent lanes. Due to inherent reduced speeds while turning, a reduced size collision box sufficiently rectifies this potential problem.

Traffic Signal Model
Now that the AI vehicles are able to detect (and avoid) collision with one another, the next step was to add logic for AI vehicles when in the vicinity of signalized intersections. This algorithm handles all decisions to be made depending on the current "status" (i.e., red (R), yellow (Y), green (G)) of each intersection. Obviously, the AI vehicles need to know the state of each signalized intersection as they traverse the virtual environment. A particular

3-bay (G-Y-R) traffic signal at a 4-way intersection has two sides, and therefore, a total of five possible basic states (i.e., R-R, G-R, G-Y, Y-G, R-G), discounting turning arrows, flashing lights, and other more advanced signal states. This state information was used in the traffic signal algorithm to decide whether to slow down and stop an approaching vehicle, or to allow the AI vehicle to continue along its current path. Each traffic signal in the environment has an index identifier, so that AI vehicles can determine: a) which traffic signal is nearest, b) which direction it is approaching that intersection, and c) what is the current state of the intersection being approached.

The traffic signal state algorithm was employed during the deceleration phase of the AI vehicles, as that is when they need to make a decision as to whether to slow down, or to continue its present motion based upon the traffic signal status. This decision influenced that the vehicle motion algorithm would either: recalculate the deceleration rate (e.g., due to an approaching red or yellow light), or completely eliminate deceleration (i.e., the light is green, and is projected to remain so). When an AI vehicle enters a deceleration phase, it calls the traffic signal algorithm to check the state of the traffic signal it is approaching. There are various scenarios which were considered in order to make the traffic signal algorithm decisions similar to authentic environment traffic signal scenarios:

- If the traffic signal state is green when the AI vehicle enters deceleration, the motion algorithm equates the deceleration of the AI vehicle to zero, which then continues traversing the intersection without slowing down.
- If the traffic signal state is yellow or red when the AI vehicle enters deceleration, the motion algorithm calculates the deceleration required to stop the AI vehicle at the intersection. Depending upon the distance of the AI vehicle from the intersection (and its current travel speed), the algorithm either instructs the motion algorithm to recalculate the deceleration of the AI vehicle required to stop the vehicle at the intersection, or to continue the motion of the AI vehicle if it is too near (or inside) the intersection.
- Another scenario considered was if the AI vehicle enters the deceleration phase, the traffic signal status is red, and the AI vehicle decides to slow down and stop. While it is slowing down, the traffic signal status suddenly turns green; the traffic signal algorithm is called again and it instructs the motion algorithm to stop decelerating, and the AI vehicle continues traversing the intersection without stopping.

A final challenge is to appropriately instruct the traffic signal algorithm the capability to handle left turns at a traffic signal (i.e., given that our simplified, preliminary traffic signal model does not include a distinct state for permitting left turn motions). To take a left turn at a traffic signal, a driver has to first yield for approaching traffic, which might be going straight or turning right. To handle this scenario, there was a need to implement a method to detect any approaching traffic at a traffic signal to decide if/when to turn. To detect approaching vehicles, as shown in Figure 6, a static rectangular zone was implemented, and placed near the intersection in conjunction with a Point-in-Rectangle test (Shklarsky, 2013). Based on the result, the algorithm decides whether to slow down (or stop) the left-turning AI vehicle for the approaching traffic to pass, or allow the vehicle to proceed and complete the turn. The algorithm sends the decision it makes to the motion algorithm, and the motion algorithm calculates the new deceleration of the vehicle. Thus, if the AI vehicle detects any oncoming traffic while approaching an intersection, it will slow down and stop at the intersection and wait for the oncoming traffic to clear before making the turn.
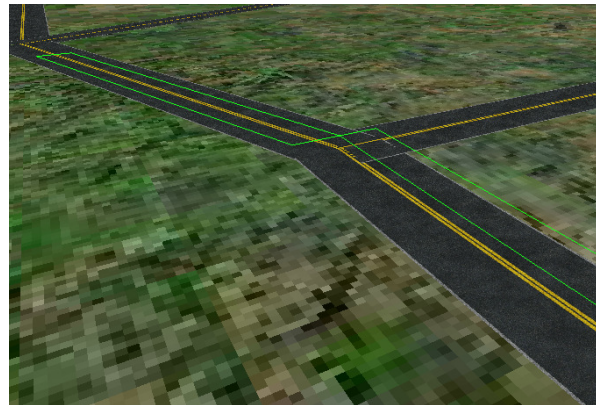

Figure 6 – Left Turn Detection   **Figure 7 – Stop Sign Detection**

Stop Sign Model

The scope of the traffic signal algorithm was expanded to include all traffic signals within the current virtual environment and its logic was extended for application at intersections governed by stop signs. The algorithm was

designed to account for "all-way" stop signs and "single-way" stop signs. For the former, the algorithm keeps track of the vehicles waiting at the stop sign, and reserves slots for each vehicle as soon as it reaches the stop sign. According to the slot reserved, each vehicle is given a "go" signal to cross the intersection. As soon as an AI vehicle starts moving through the intersection, a programmer indicator internally denotes that the intersection is occupied, and the algorithm waits for that vehicle to clear the intersection. Subsequently, a "go" signal is provided to other vehicles waiting at that intersection in the same sequence in which slots were first reserved (i.e., similar to actual driving). To accommodate single-way stop signs, some modifications had to be made to this algorithm. Specifically, a function was added that could detect vehicles in the opposite (oncoming) lane (i.e., to that driven by the stopped AI vehicle), so that a decision can be made whether it would be safe to move to the oncoming lane. In fact, similar logic was used as to detect approaching traffic for left turns in the traffic signal algorithm. As such, a rectangular detection zone was created, as shown in Figure 7, to monitor a portion of the oncoming lane approaching the stop sign, the length of which is dependent upon the posted speed limit in the destination lane. If there are detected to be other vehicles in this zone, then the stopped AI vehicle waits for the traffic to clear before proceeding into the oncoming lane. The algorithm was designed with the intelligence to look for vehicles in a particular stop sign zone depending upon whether the stopped AI vehicle is flagged to turn left or right at the stop sign. If the AI vehicle is planning to take a left turn, the algorithm checks for vehicles in both zones, and if the AI vehicle is planning to take a right turn, then the algorithm checks for vehicles only in the zone covering the right lane.

Lane-changing model

Lateral movement (e.g., lane changing) by AI vehicles is necessary to represent real environment traffic scenarios. For example, the AI vehicles in the left-most lane will take a left turn at an approaching intersection, vehicles in middle lanes will continue straight, and the vehicles in the right-most lane will turn right (or go straight). These decisions were made using stochastic effects, as each AI vehicle approaches each given intersection. For an AI vehicle to change lanes, the heading angle no longer conforms to the (global) heading angle with the street upon which the vehicle is traveling. To assure that the lane change appears fluid, the lane changing function increments this heading angle in small amounts (heuristically chosen to be approximately 2.5 degrees) at each frame rendering, as demonstrated in Figure 8. As described previously, a 60 Hz. update rate is employed.

As a component of designing the lane changing algorithm, there was a need to add logic so that the AI vehicles follow all traffic laws while in a state of lateral transition. To prevent disturbing traffic while lane changing, the AI vehicles have to detect other vehicles in the lane into which it is planning to move, and make appropriate decisions based on the speed and distance between the vehicles. To achieve this, collision boxes were implemented to detect other vehicles in the vicinity (i.e., in front and behind, and to the left and right) of the AI vehicle in transition. Therefore, additional collision boxes were added on the left and right side of each AI vehicle, as shown in Figure 9, that check for collision in the lanes on both sides of the lane-changing AI vehicle. The lane changing collision boxes move along with the AI vehicle. The calculations for these collision boxes are performed similarly to those used for the standard collision detection algorithm, and detect vehicles in the next lane before a lane changing decision is made. If there are vehicles detected in the lane changing collision box, then the lane changing algorithm waits until the traffic is clear to change lanes.
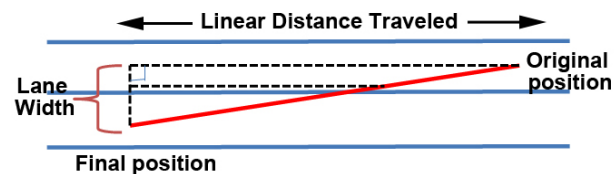

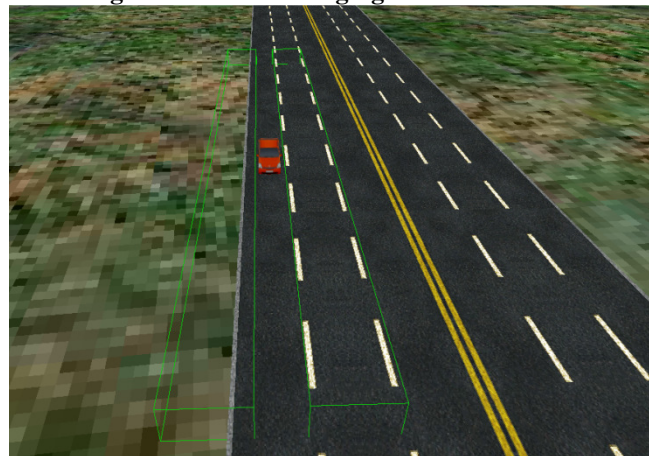
Figure 8 – Lane Changing Transition Zone

Figure 9 – Lane Changing Collision Detection

With the above-described core components (i.e., linear motion, collision detection, street lights, stop signs, and lane changing) to the AITM developed, the preliminary model was pilot tested. During that process, a number of imperfections in the model were detected that required improvement, and are described in the next section.

AITM (REVISIONS AND IMPROVEMENTS)

Once the preliminary model was designed, we were able to perform in-house testing and validation to observe the operability of the AT Traffic Model. In so doing, a number of deficiencies were noted that were difficult to forecast during the initial development phase. Three such deficiencies are described and illustrated here with some detail, along with brief descriptions of how these model deficiencies were ultimately improved, or circumvented altogether. Perhaps by offering these challenges, we will provide insight for future application developers in transportation-based M&S who might face similar difficulties.

Non-conventional road geometry. Certain intersections within the virtual environment, like that shown in Figure 10, were such that the participating streets were not at orthogonal angles. (Acute angles were of particular concern). This caused problems when AI vehicle collision boxes would (unintentionally) impede on adjacent lanes of traffic. As a result, we began to use collision boxes of dynamic length. In this way, the size of the collision box would increase with speed, and would also decrease during radial (as opposed to linear) motion. The idea being that when an AI vehicle is turning, speeds will be inherently low, and therefore, the risks for a collision somewhat reduced.
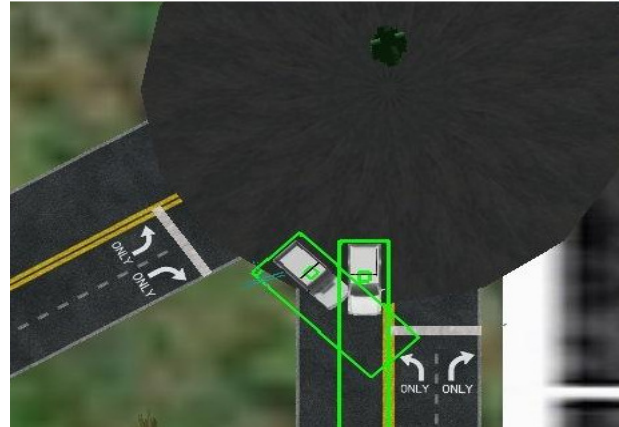

Figure 10 – Odd-shaped intersection

Vehicle stacking at left turns. As previously described, the AI vehicles have been programmed to make random decisions upon approaching intersections to turn left or right, or proceed straight through. Left turn logic was particularly problematic to handle robustly. Often times, such as shown in Figure 11, on single lane streets (i.e., those with no explicit turning lane), vehicles would stack (queue) for excessively long distances waiting to turn. Ultimately, we minimized this problem by reducing the random likelihood of left hand turns at these problematic intersections, and also by decreasing the required gap for an AI vehicle to decide to instantiate the turning motion. The combination of modifications improved overall performance.

Figure 11 – AI vehicles waiting to turn

Interactions with AI vehicles and the human-driven vehicle. In addition to the AI vehicles, once a human driver was added to the loop (i.e., one who doesn't always make "idealized" decisions), various difficulties had to be overcome. For example, as shown in Figure 12, a human driver might stop suddenly or accidentally drive in the wrong lane. Ultimately, this necessitated subtle case-by-case modifications to the model (e.g., max/min deceleration rates; default sizes of the collision boxes) to account for "special case" incidents of this nature.
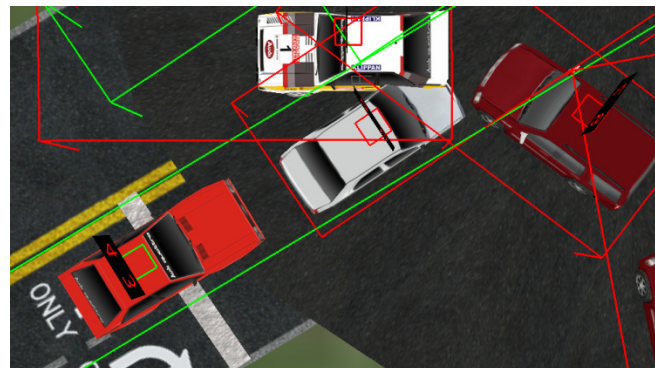

Figure 12 – AI-Human Interactions

CONCLUSIONS

Roadway safety and sustainability continue to be major public health concerns, and subsequently, simulators (and other M&S technologies) continue to become more abundant in a wide variety of Intelligent Transportation Systems

(ITS) research applications (e.g., autonomous driving, human factors, and rehabilitation). To confront these problems, standalone simulators are often implemented as an analysis and decision-making tool. Driving Simulators (e.g., to monitor driver behavior, performance, and attention), and Traffic Simulators (e.g., to plan, design and operate transportation systems) have been employed with some success. However, while traffic simulation models allow for capturing dynamics of full-scale traffic networks, they often lack behavioral realism. Furthermore, in a majority of driving simulators, accompanying traffic is pre-programmed and does not react according to the real-time actions of the human subject operating the simulation. Related research has noted that existing microscopic traffic simulation models (i.e., those based on available car-following, gap-acceptance, and lane-changing models) often lack the level-of-detail required for safety evaluations, which demand models that more accurately reflect errors in drivers' perception, decision-making, and actions.

Largely for these reasons, an Artificially Intelligent Traffic Model (AITM) was constructed to operate in conjunction with a custom-designed driving simulation environment. The framework presented in this paper has been designed as an alternative for commercial "microscopic" traffic simulators, whose operability is often more concerned with gross en masse vehicle behavior, with individual vehicle movements that are not fluid, and therefore not suitable for integration with live human subjects. The preliminary development of the core components (i.e., linear motion, collision detection, street lights, stop signs, and lane changing) of the AITM was described in detail. Subsequent to pilot testing, the complexity of the interactions between the various model components was noted, and therefore required critical revisions to the baseline AITM model, which were described and illustrated.

FUTURE WORK

While vehicle and transportation network technologies continue to evolve, there is an increasing urgency for improved fidelity for driving/traffic simulation research. As such, the research described here can be expanded and improved, and to conclude the paper, a few detailed suggestions are offered here.

a) **Implement customized human behavior models to enhance the traffic mobility**. The proposed concept is to override the (artificially intelligent) driver behavior model with experimentally attained, subject-specific human behavior performance models. Given a particular set of driver profiles and environment settings, researchers could customize different response profiles to better mimic human behavior (e.g., human response to warning messages from the infrastructure) thus improving the realism of their experiments.

b) **Provide a high-fidelity, multiple-participant capability to facilitate research that involves real-time interaction between human participants**. Two or more driving simulators should be able to connect in real-time, which would enable human drivers to interact with each other. Despite the success of driving simulators such as DiVE (Prendinger et al., 2014) that have already provided certain level of multiple driver capacity, there is still room for improvement in terms of functionality and fidelity. A robust game-inspired multiple-participant environment is essential to analyze the incremental development of scenarios when both automated and human-driven vehicles are on the road simultaneously.

c) **Integrated Traffic-Driving-Network Simulation**. The microscopic traffic model presented in this work has been the first step towards the development of a more complete integrated simulation environment for transportation research. While there have been attempts to develop integrated two-way simulators (e.g., traffic-driving, traffic-network), none have attempted to integrate all three. To this end, a 3-in-1 Integrated Traffic-Driving-Network Simulator (ITDNS) is currently under ongoing development (Zhao et al., 2013).

d) **Expand capabilities for Military geography/topography**. Although the work presented here is intended primarily for a fleet of vehicles in civilian driving simulation (and assuming primarily **flat** elevation), extensions could be envisioned for off-road military applications. As an example, a variety of uneven terrain types (e.g., desert, mountain, jungle/forest, mud) are prevalent in today's ongoing combats, and each category has a unique climate that provides combatants with different obstacles.

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