Cognitive Aspects of Traffic Simulations in Virtual Environments

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Abstract. Using virtual environment systems for road safety education requires a realistic simulation of road traffic. Current traffic simulations are either too restricted in their complexity of agent behavior or focus on aspects not important in virtual environments. More importantly, none of them are concerned with modeling misbehavior of traffic participants which is part of every-day traffic and should therefore not be neglected in this context. We present a concept for a traffic simulation that addresses the need for more realistic agent behavior with regard to road safety education. The two major components of this concept are a simulation of persistent agents which minimizes computational overhead and a model of cognitive processes of human drivers combined with psychological personality profiles to allow for individual behavior and misbehavior.

Introduction

Traffic simulations for virtual environments are concerned with the behavior of individual simulated traffic participants. The complexity of behavior in these simulations is often rather simple to abide by the constraints of processing resources. In traditional traffic simulations - used for road planning or traffic jam prediction - the behavior of individual traffic participants is also modeled, but the focus lies on the emerging overall behavior of the entire system, e.g. to identify possible bottle necks of traffic flow [29].

One objective of the FIVIS project [14,15] is to create a realistic bicycle simulator for road safety training of children. For that the traffic agents need to be persistent and react realistically to changing environmental conditions in real-time. Within virtual environments, traffic simulations need to be realistic only within a certain range of the visualization setup's viewing frustum. If simulated content is not directly visible, there is no need to spend major computing resources on its calculation.

Training simulators are widely used to increase safety in almost all areas of modern transportation (car, train, plane, etc.). With their help trainees are taught how to behave in dangerous situations without the risk of causing physical harm. The FIVIS project attempts to apply this advantage to bicycles, as there seem to be no such simulators commonly available today. Figure 1 shows the current system. So far dangerous traffic situations are realized in general by scripted events, defined for each car or any other traffic agent. This process is tedious, inflexible and might require trainees to follow a specific route. Additionally, subjects will memorize scripted events. Thus, they will not learn how to generally react to dangerous events, but rather how to react to specific actions performed by agents in certain situations at predetermined locations.

Figure 1. The FIVIS bicycle simulator is an immersive multi-screen system providing consistent 3D information to the visual field of subjects. Input (steering, acceleration, deceleration) is provided using a real bicycle fixed to the ground.

Thus, for the simulation of traffic agents in virtual environments, a cognitive traffic modeling approach is proposed that combines techniques from the field of traffic research and cognitive architecture research to address the stated challenges within a project called AVeSi

('Agentenbasierte Verkehrssimulation mit psychologischen Persönlichkeitsprofilen' – engl. 'Agent-based traffic simulation with psychological personality profiles').

This contribution will present a concept which aims at achieving the criteria stated above. It is structured as follows. The next section will summarize existing approaches. Following is the presentation of the developed concept that includes the discussion of how to achieve persistence in the simulation in Section 2 and the discussion of how to model cognitive traffic agents in Section 3. Finally, conclusions are drawn.

1 Related Work

The AVeSi project aims at developing an autonomous traffic simulation as an extension to the FIVIS bicycle simulator. The concept developed to fulfill this objective is based on previous research by Kutz et al. [17] who planned to utilize psychological personality profiles for traffic agents in virtual environments. The strict computational limits of virtual environment applications, such as digital games, often restrict the complexity of agent behavior in this domain. This fact has caused developers to utilize rather simplistic and static methods. Only in exceptional cases is increased realism attempted by utilizing adaptive artificial intelligence (see e.g. [1] and [27]).

In the field of cognitive architecture research, the ambitious goal is to create artificial intelligence able to solve general problems. Numerous attempts have been made to achieve this goal with varying concepts. The most prominent examples are the *Soar cognitive architecture* and ACT-R. The major difference between both is the type of memory and learning used. Soar is a *symbolic architecture*, which means an agent represents its environment and reasons about it using symbols [18]. ACT-R is an approach which uses elements of symbolic nature as well as elements of *emergent architectures*. Emergent architectures do not symbolize the knowledge of an agent, but instead utilize networks of distributed processing elements, typically emulating human brain structures [4,6]. Another example, called ICARUS [19], was already applied to the domain of in-city driving. The application was mainly concerned with basic driving behavior such as lane alignment or deceleration before turns. In [21] a cognitive architecture was introduced to simulate attention mechanisms of pilots and drivers to test assistance systems.

However, despite modeling erroneous behavior, its influence on decision-making was not addressed.

In contrast to traffic simulations in virtual environments, traditional traffic simulations have been researched since the 1930s. In [29] an overview of various approaches is provided. In this field, the behavior of a single traffic agent is usually not of interest to the researchers. Nevertheless, detailed and evolved descriptions of basic driving behavior, like the Intelligent Driver Model (IDM) [28], provide numerous starting points for cognitive traffic agents.

The field of traffic simulation also uses input from other disciplines. For example, in queueing theory, the formation and behavior of queues is analyzed mathematically. This includes the process of arriving at the back of the queue, waiting in the queue as well as being serviced at the beginning of the queue. Basic components of a queueing model are the queue and a servicing station. An example often used in the literature is a post office (e.g. [3]). Customers queue to be serviced at a counter. The time spent in the queue is dependent on the queue's length and the servicing rate of the servicing station. This queueing model can also be used to simulate traffic. Here the roads are modeled as queues and the servicing stations are junctions. Heidemann [12] and Vandaele [30] both developed basic frameworks for queueing-based traffic simulations. In [9] Gawron introduced a simple queueing model called *FastLane*, which is capable of modeling spill-backs by restricting the amount of vehicles in a queue and the amount of vehicles that can leave the queue.

2 Persistent Traffic Agents

An obvious way to save computational resources in traffic simulations for virtual environments is to remove traffic agents from the simulation once they leave the user's field of view (see Figure 2). This approach can lead to situations which are irritating to a user, but simulating all agents at all times would be too costly. Thus, the idea is to combine a detailed microscopic simulation within the user's vicinity with an additional coarser simulation level for non-visible traffic agents.

2.1 Queuing-based Traffic Simulation

At first, methods like treating traffic as fluid and applying smoothed particle hydrodynamics (SPH) to approximate common numerical solutions (cf. [23] and [24]) or applying macroscopic traffic models (e.g. the Lighthill-

Whitham-Richards model [20,22]) were investigated. Both approaches proved to be unsuited for the needs of the AVeSi project. Therefore, it is proposed to use a microscopic traffic model based on a queue-representation for the second simulation level (cf. [5,8,10,26,30,31]).

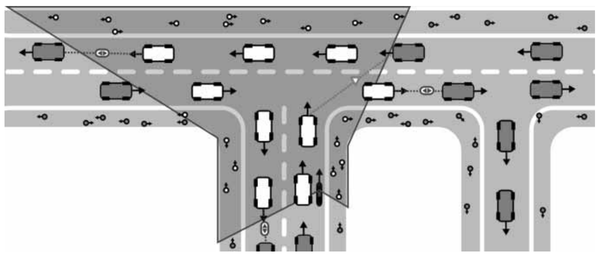

Figure 2. To save computational resources, traffic simulations in virtual environments usually simulate only agents within the user's field of view (white). The goal is to also simulate non-visible agents (gray) with less detail to achieve persistence with minimal computational overhead (image based on [17]).

As a queueing model, the *FastLane* model of Gawron has been chosen because it is a simple approach that provides meaningful approximations of travel times similar to those calculated by the well-known Nagel-Schreckenberg model as well as the inclusion of spill-backs [5,9]. Here the road network is represented by a directed graph $G = \{V, E\}$; where vertices V represent junctions and edges E represent roads. Each is modeled by a "physical queue", meaning a queue with limited space. Figure 3 presents an example for such a queue-based network. Each queue representing a road features a capacity C (maximum amount of vehicles that can leave a queue in one simulation time step), a length L, a number of lanes n_{lanes}, and a free flow velocity v_0 (the desired velocity a vehicle can drive or the maximum velocity allowed on that road).

When a vehicle enters a road, the vehicle's length of stay on this road is calculated. This time is called *travel* or *duration time* and depends on the free flow velocity and the current utilization of the road. After this time, the vehicle can reach a junction. Whether it does in fact reach the junction depends on the capacity of the road and the space on the junction.

In an initial approach, junctions will be modeled as either signalized or unsignalized and vehicles will be distributed randomly to connected roads. More sophisticated strategies to distribute vehicles at a junction can be found in [11] or [13].

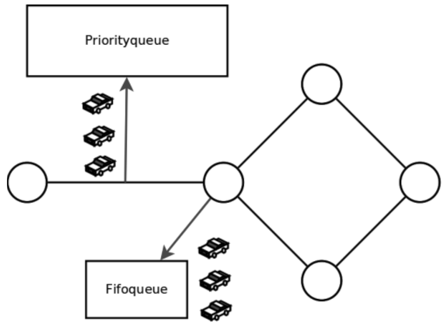

Figure 3. An illustration of how vehicles are represented in a queue-based road network. Roads are modeled as priority queues, where the priority is given by a vehicle's duration time. Junctions are servicing stations containing FIFO queues for each outgoing road [9].

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2.2 Linking Simulation Levels

The challenge of the queueing-based approach lies in determining the exact spatial position of a vehicle on the road and on modeling how one vehicle passes another vehicle within the queue. Accurately determining the spatial position of a vehicle is important for transitioning the vehicle from the coarser simulation level into the finer simulation level for visualization. Further, it is important to determine the fringe between these two levels. The vicinity, in which agents are simulated with the highest detail, should be as small as possible to save computational resources. On the contrary, it should be large enough to avoid unnecessary transitions between both levels and visual inconsistencies like sudden appearances of agents within the visual field.

Passing vehicles have to be incorporated into the simulation to be able to take different desired velocities and special vehicle behavior into account, e.g. a post office truck that stops every few hundred meters. Such vehicle behavior is necessary as disruptive factor for regular traffic, creating potential for risky decisions and dangerous situations.

3 Cognitive Traffic Agents

To achieve a realistic traffic simulation, artificial agents should not only be persistent within the simulated environment, but also need to show misbehavior like their human counterparts. However, they must do so only in situations where it really makes sense to an observer. Therefore, the authors believe that it is not enough to deviate from "normal" behavior by introducing fuzzy logic or random events, which is done frequently (e.g. see [7]). Instead an agent must consider its current perceivable situation when determining its actions. While doing so, it should also have the ability to calculate and take risks.

For this purpose the relevant cognitive processes should be modeled to induce realistic human behavior in traffic (e.g. perception, anticipation, decision making, etc.). Particularly modeling the influence of risk propensity on action selection will be a central aspect of the project. An agent choosing a risky action to reach its goals could cause it to break a traffic rule. Such misbehavior would result in potentially dangerous situations for other traffic participants such as a trainee using the FIVIS simulator.

3.1 Psychological Personality Profiles

The foundation of the agents' behavior will be a psychological personality profile as suggested in [17]. Such profiles will be based on the "Five Factor Model (FFM)" from psychology. According to this model, a human personality can be defined by a set of five distinct character traits: openness, conscientiousness, extraversion, agreeableness, and neuroticism. To determine a personality, a score for each trait can be extracted from standardized tests such as the Neo-Five-Factor Inventory (NEO-FFI) [2].

In [16] Herzberg argues that it is difficult to directly correlate driving behavior with the personality traits of the FFM. However, he found that such a correlation exists for the personality prototypes *undercontrolled*, *overcontrolled*, and *resilient*. Based on Herzberg's research a specific traffic situation has been designed for evaluation purposes that cannot be handled by regular, rule-based agents typical for virtual environments. In this scenario, a closed road system with an uncontrolled four-way intersection was modeled and traffic was simulated using an implementation of the Intelligent Driver Model (cf. Figure 4).

Agents arriving at the intersection need to yield to agents coming from the right. If, for example, four agents arrive at the intersection from each direction, each has to yield to another one resulting in a deadlock. The scenario described above, provided a road of about one kilometer in length with lanes in each direction. The maximum capacity of the network was about 500 vehicles. As illustrated by Figure 5, even at 3% of the maximum capacity (15 vehicles) it took only 333 seconds on average for a deadlock to occur. At 5% capacity and above, deadlocks appeared after less than one minute. The average and median times depicted in Figure were based on 15 simulations for each specified number of vehicles (15, 20, 25, 30, and 35) each starting with a random distribution of vehicles within the road network.

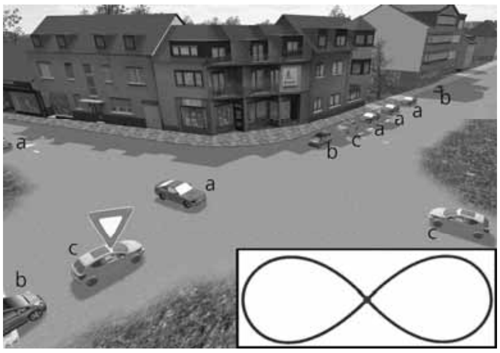

Figure 4. To evaluate agents with personality profiles, a closed road system with an uncontrolled four-way intersection was modeled. Vehicle types represent psychological prototypes: *undercontrolled* (a), *overcontrolled* (b), and *resilient* (c). The scene depicts a resilient driver waiving its right of way (indicated by a yield sign) allowing the driver on its left to cross the intersection, which resolves the deadlock (image based on [25]).

To resolve the issue we have augmented the agents with a mechanism to perceive such deadlocks (including a basic model of visual perception) and a personality profile assigning them to one of the three personality prototypes. According to Herzberg's findings we determine which of the four agents gives up its right of way based on its prototype. With these modifications, deadlocks can be detected and resolved, allowing the simulation to keep traffic flowing (cf. Figure 4).

Further detail and results which can be found in [25] indicate how personality profiles can be used to model individual behavior. In future revisions of the current realization, the profiles should also contain a dynamic component such that the behavior influenced by the agent's personality can be altered during the simulation, for example based on prolonged waiting times.

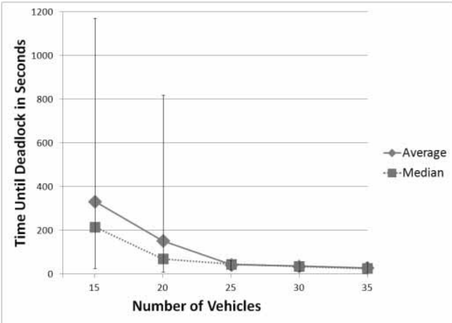

Figure 5. Average and median times until the simulation of the uncontrolled four-way intersection resulted in a deadlock. Vertical lines depict the longest and shortest times. (Image based on [25]).

3.2 Cognitive Processes

To further increase realism of agent behavior the application of ideas from cognitive architecture research is anticipated to yield the desired results. While the ultimate goal of this field is far more ambitious than what is necessary for the project presented here, the general ideas should provide an ideal starting point for cognitive traffic agents. Figure 6 illustrates an example of a cognitive traffic agent. It features typical modules from cognitive architecture research as well as an underlying personality profile based on the FFM (cf. Section 3.1). The most important aspects of such an agent are its links to the surrounding virtual environment, i.e. its perception and its actions.

In a first attempt to model human perception, a field of view was modeled using a geometric representation within a 3D game engine. Only agents and objects which enter this geometry are visible to the agent if they are not occluded by other objects. In the future this simple model could be extended by concepts of attention selection and attention division as presented in [21] and even audio cues. Especially by incorporating attention mechanisms, other modeled cognitive aspects, like emotion or the memory, could also influence the agent's perception. Additionally, as is the case in reality, the driving behavior might also be influenced by additional factors, such as age, gender, time of day, weather, road properties, and more. Most importantly, in combination with the personality profile, the modeled processes – in particular the decision module – should provide a means to encourage agents to take certain risks while trying to achieve their goals.

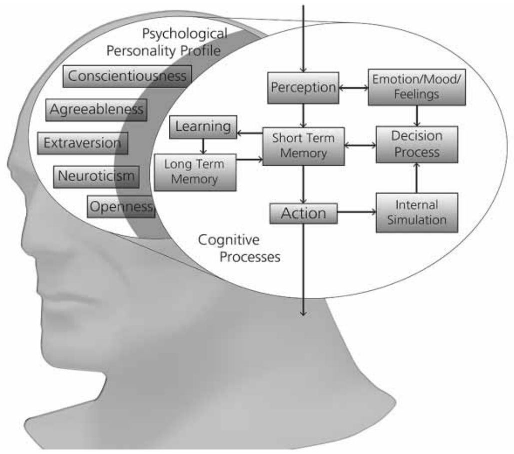

Figure 6. A possible model of a cognitive traffic agent for virtual environments containing the depicted modules from cognitive architecture research. An additional layer with a psychological personality profile may influence all cognitive processes (image based on [25]).

4 Conclusions

In conclusion, modeling persistent traffic agents whose behavior is inspired by human cognitive processes might improve road safety training applications, since they reflect real world traffic conditions more realistically. Especially, the ability to perform risky actions leading to agents breaking traffic rules and creating dangerous situations for other traffic participants should increase the realism of such a simulation. To achieve this goal, many issues remain to be solved. For example, what is the most suitable way for an agent to represent its surroundings internally or does an agent need to learn during the simulation? Other problems are of practical nature, like the question of how much overhead is created by constantly transferring agents from one simulation level to the other. Realizing and evaluating the current ideas presented in this article might be challenging, but if successful, other driving/traffic simulators and in particular traffic simulations in digital games will benefit from this research as well.

Acknowledgments

The FIVIS project received additional funding from the Deutsche Gesetzliche Unfallversicherung (grant FP-307). The AVeSi project is being funded by the FHprofUnt program of the Federal Ministry of Education and Research (grant 17028X11).

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Submitted: March 2012
Revised: June 2012
Accepted: August 1, 2012