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Agent-Based Simulation of Drivers with the Janus Platform

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Abstract

Agent-based models may be now used for modeling complex transportation systems. They permit the analysis and the understanding of the complex phenomenon of interactions between different entities. This paper proposes a multiagent model for the microscopic simulation of drivers in a virtual environment. It is based on the definitions and constraints coming from the agent-oriented software engineering. The paper proposes to make a clear distinction between the models of the individuals (the drivers), and of the physical environment in which the agents are located. This distinction permits to decrease the design's complexity. The selected agent platform to support this model is Janus, and its environment model JaSim.

Keywords: Multi-agent simulation, Environment model, Driver model, Janus Platform, JaSim environment model

1. Introduction

An agent-based model (ABM) is a class of computational models for simulating the actions and interactions of autonomous agents with a view to assessing their effects on the systems as a whole. ABM is now widely used for modeling increasingly complex systems. Application of ABM is not only limited to the computer science domain. Currently, many research areas such as transportation behavior modeling, need to analyze and understand the complex phenomenon of interactions between different entities. While traditional modeling tools cannot catch the complexity, ABM can do it through modeling the interaction of autonomous agents and deducing the rules for such a system. We, therefore, in this paper propose an agent-based model for the simulation of drivers in an urban environment. Plenty of models in the literature provide tools for simulating drivers from the microscopic level to the macroscopic level. Many of them are used an agent-based approach to support the individual characteristics of the drivers [1]. *The purpose of this paper is not to provide a novel model for drivers, but to make a proof of implementation on a general-purpose agent platform.* This platform is respecting the definitions and the constraints that are generally assumed in

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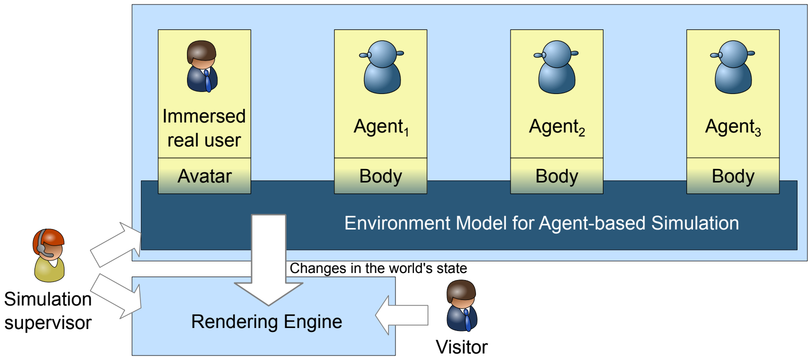

Figure 1. General architecture of the simulator for a virtual environment

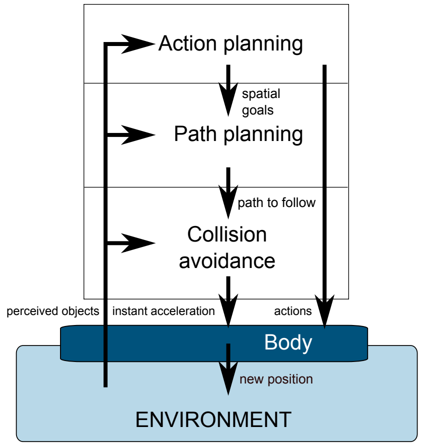

Figure 2. Layered architecture of an agent

the agent-oriented software engineering and agent-oriented simulation (principles of autonomy, locality, body/mind separation. . .), but skipped by a part of the traffic-oriented platforms. These principles ease the creation of simulation tools, and cyber-physic systems with the same model's implementation. Our proposition is based on the multiagent agent platform Janus[1], and on the virtual environment model JaSim[2]. We propose to make a clear distinction between the agents, and the physical environment in which the agents are located. This paper also describes the driving behavior of each agent.

This paper is structured as follows: Section 2 provides an overview of the simulation model. The model of the physical environment is described in Section 3. Section 4 details the model of the drivers. Several experiments are presented in Section 5. Section 6 concludes this paper and provides perspectives.

2. Overview of the Simulation Model

The models for multiagent simulation are composed of four parts[3,4]: (i) *Behaviors of the agents:* modeling of the deliberative processes of the agents, (ii) *Interactions:* modeling the actions and the interactions among the agents, (iii) *Environment:* specification and definition of the objects that make up the simulated world, as well as the endogenous dynamics of the environment, (iv) *Scheduling and running:* modeling the passage of time, and definition of the agents' scheduling. The boundary between what is considered as an agent and what is considered as part of the environment depends on the considered problem. However, agents always represent the active components of the studied problem.

A number of basic principles should be followed to ensure the quality of a simulation and limit through simulation: (i) respect the integrity constraints of the environment, (ii) respect the constraint of locality agents, (iii) a clear distinction between the body of the agent (state variables beyond the control of the agent and part of the representation of the agent in the environment, *e.g.* its speed, position. . .), and the mind of the agent (the state variables under the control of the agent, for example, emotionalism, its goals, motivations. . .)

We propose a simulation model respecting these principles to create simulation models of individuals in virtual worlds. The architecture of our model is shown in the upper part of Figure 1. Each agent can interact with other agents, either directly or by stigmergy. The agent can perceive and act on the physical environment through its representation in it: *its body*. The lower part of the figure shows the display software. Note the presence of an "avatar." The avatar is a representation of a real human user in the simulated universe. To ensure the consistency of the interactions between the avatar and the agents populating the universe, the avatar is subject to the same constraints

[1] `http://www.janus-project.org`

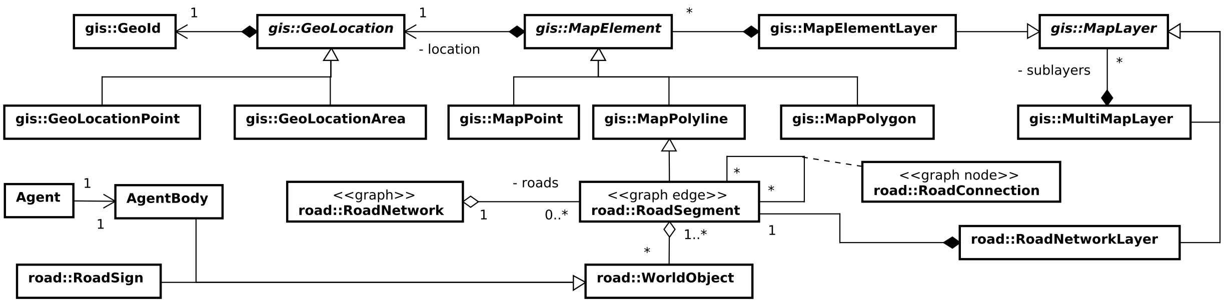

Figure 3. Class diagram of the 1D Environment

as the bodies of the agents (imposed by the principles above): the avatar respects the laws of the virtual world, and cannot act outside their boundaries.

3. Environment Model

The environment is widely regarded as one of the essential parts of a multiagent simulation. However, there are different perspectives on the role it plays in a multiagent system and its definition. Environments used in our work can also be considered as special cases of “physical environment”[5,6]. The notion of “physical environment” refers to the class of systems in which agents and objects have an explicit position. Actions, and perceptions are also localized[7]. The missions of the environment in a multiagent simulation are proposed by[8]: (i) The environment is shared by the agents, where each perceives from and acts inside. (ii) The environment manages simultaneous and joint actions of agents, and the preservation of the environmental integrity. (iii) The environment must be locally and partially observable. (iv) The environment is an active entity; it can have its own processes, regardless of those agents.

The proposed environment model is a model of the environment dedicated to the simulation in virtual environments in 1D, 2D or 3D. It is considered inaccessible, non deterministic, dynamic and continuous[9]. It is primarily designed for the simulation of crowds and traffic. The model combines the agent-oriented organizational approach from[10] with object-oriented structures and algorithms conventionally used in the fields of virtual reality and video games. This model is designed to provide mechanisms of realistic perceptions and actions to agents. It is a software framework providing a collection of well-known and suitable tools for the easier implementation and efficient crowd and traffic simulation.

In this section, we present the concepts used to build the model of the urban environment. Figure 3 shows the class diagram describing these concepts and their relationships.

The model is inspired by the urban environment of geographical information systems (GIS). Basically, it holds the map data in a collection of layers. Each layer contains a data type: roads, public buildings, schools, areas of high population density. . . Data associated with a layer are geometrical shapes named map elements. In Figure 3, the elements of the urban environment are defined in the package `gis`. Roads are a specific subset of GIS objects. All routes form a graph consisting of the segments of roads (`RoadSegment`) and the connections between them (`RoadConnection`).

Because the road network is a central data structure in our model, we propose to use spatial data structures (quadtree) and the associated algorithms for an acceptable access complexity[2] to elements of the road network. This structure is required when queries should be made from spatial criteria to overcome the complexity associated with the graph structure of the road network[11].

[2] $O(\log_4 n)$ where n is is the number of cells resulting from the discretization of the environment in the form of an irregular grid.

4. Driver Behavior

The architecture used to model agents is composed of three layers, as shown in Figure 2:

- **Strategy Layer:** At the strategic level, individuals decide on the activities to be carried out in the universe. While some of these activities may be discretionary (*e.g.* buying a newspaper), others may be mandatory (validating a ticket before entering the train). All choices can be linked to environmental characteristics (type and location of stores…) In this layer, agents typically use an architecture for selecting actions such as the Belief-Desire-Intention (BDI) architecture or the Goal-Oriented Action Planning model[12].
- **Tactic Layer:** Decisions at the tactical level concern the short or medium term. They must be taken by the agent with the decisions at the strategic level as reference. From the objectives given by the latter, the model of the tactic layer must build a detailed action plan. The locations of the different activities and the paths to reach these locations are determined at this level. The BDI architecture can be used to construct the sequence of actions. Shortest path searching algorithms can form the basis for calculation of routes: A*[13], D*[14].
- **Operation Layer:** At the operational level, individuals take decisions in the short term. These decisions are guided by those provided by the previous layer. The features within this layer decide the trajectory of an individual, the speed or acceleration. Unlike[15], who considers only the choice of the best speed for an individual, we believe that the main objective of the individual's model is to avoid collisions with the objects and the other individuals in the surrounding environment. In other words, we consider that the models in the operational layer aim to determine the movements and actions that will make the body of an individual.

There are interactions between the models for each decision level. Figure 2 provides an example of interactions between the layers constituting a simulation model of the driver. This architecture is also used for the simulation of pedestrians and cyclists in virtual cities[16,17,18], in railway stations and airports[19,20], to simulate the evacuation of a building in case of fire[21].

To simulate drivers, the agents should decide the instant acceleration of the vehicle at any time t. The intelligent driver model[22] is a time-continuous car following model for the simulation of freeway and urban traffic. It describes the dynamic of the positions and velocities of a vehicle. The initial model is adapted to discrete time progression by evaluating one of the two following equations at each time step: the free road $\dot{v}_\alpha^{\text{free}}$, and the interaction $\dot{v}_\alpha^{\text{int}}$ terms, which are detailed by Equations 1 and 2, respectively. The first one is used when the distance to the next obstacle is superior to a certain threshold, which is equivalent to an absence of an obstacle. The second term is used when there is an obstacle close enough to have to adapt the speed according to this obstacle.

$$\dot{v}_\alpha^{\text{free}} = a\left(1 - \left(\frac{v_\alpha}{V_\alpha}\right)^\delta\right) \quad (1) \qquad \dot{v}_\alpha^{\text{int}} = -a\left(\frac{s + v_\alpha T}{d} + \frac{v_\alpha \Delta v_\alpha}{2d\sqrt{ab}}\right)^2 \quad (2) \qquad V_d = \frac{102}{1 + \frac{346}{R^{1.5}}} \quad (3)$$

V_α and v_α are the maximum speed and the speed of the vehicle α, respectively. a and b are the maximum comfortable acceleration and deceleration. T is the desired time headway to the ahead obstacle. s is the safety distance between two vehicles. d is the distance from α to the ahead obstacle. δ is a constant usually set to 4.

To determine the maximum speed on a portion of the road, the driver mainly read the traffic signs. However, there is a case where the agent should drive bellow the speed limit: turning at a crossroad, following a curved road. Consequently, the maximum comfortable speed under these conditions should be computed. This speed is based on the V_{85}[23] speed: the speed below which 85% of the people drive. The comfortable speed is computed by Equation 3 from[24], where R is the radius of the road curve.

5. Experiments

Experimentations were done on a population of 3000 people (input data from interviews). One of the major goals of our experimentations is to compute and possibly optimize the (complex) agent-based reproduction of the drivers. The trips are extracted from the data gathered by public interviews in the city of Belfort (France). Figure 4 illustrates

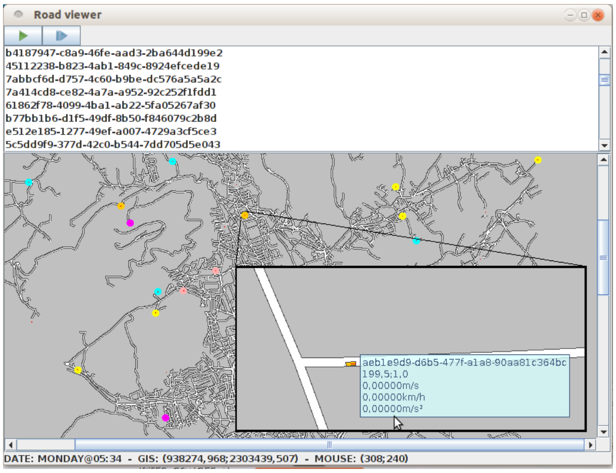

Figure 4. Screenshoot of the simulator on the JaSim

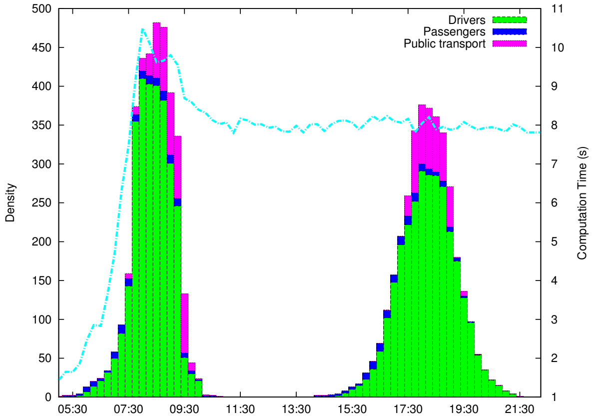

Figure 5. Repartition of the transport modes during the reference day

the simulator window. Figure 5 gives the histogram of the repartition of the selected transport modes during for every quarter of hours during the reference day. The passengers represent 4% of the population. This amount includes carpooler[25], and people from the household of the driver. The population that is using the public transport mode corresponds to the people who have not succeeded their carpooling negotiations. It is mainly due to too constrained time windows. Figure 5 illustrates the computation time of the simulation. This curve depends on the numbers of launched agents. When the number of agents is stable, the computation time is stable too.

6. Conclusion

This paper provides a brief overview of the simulation model of drivers on the Janus and JaSim platforms. The model is based on the distinction between the model of the urban environment and the models of the agent s' behaviors. The influence-reaction model[7] is adapted and applied to support coherent interactions between an agent and its physical environment. This interaction is supported by the representation of the agent in this environment: its body. This model permits to reproduce the behavior of the drivers according to the public interviews, which are available for the individual mobility within the region of Belfort (France). Our model has scalability issues that are still to be solved. Apart from scalability issues, future research will focus on enhancing the driving behavior by introducing better acceleration computations, lane-changing algorithms. . . Another major perspective is to translate the model to the SARL multiagent language[3] and its related platform Janus-2 [4], and to compare the results to a model running on GAMA[5] or MATSIM[6].

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The JaSim model and related tools are contributing to the Simulate commercial offer of the Voxelia SAS[7] company, France. The views and conclusions contained in this document are those of the authors, and should not be interpreted as representing the official policies, either expressed or implied, of the Voxelia SAS.

[3] http://www.sarl.io
[4] http://www.janusproject.io
[5] https://code.google.com/p/gama-platform/
[6] http://www.matsim.org/
[7] http://www.voxelia.com

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