

The Use of Norms' Violations to Model Agents' Behavioral Variety

Benoit Lacroix^{1,2}, Philippe Mathieu², and Andras Kemeny¹

¹ Renault, Technical Center for Simulation
Technocentre - 1 avenue du Golf
F-78288 Guyancourt Cedex, France

² LIFL CNRS UMR 8022
University of Sciences and Technologies of Lille
Cite Scientifique Bat. M3
F-59655 Villeneuve d'Ascq Cedex, France

Abstract. In multi-agent applications, normative systems are usually used to regulate the behavior of the agents. They provide an efficient means to ensure limited deviations from an expected ideal behavior. Many works have been done in this classical research direction, less frequent are the works on norms in simulation. In this paper we focus on simulations of spatially situated agents, typically moving around simulated physical environments. Our goal is to provide a mechanism to generate efficiently consistent agents' characteristics. We propose to model behavioral differentiation in such simulations as a violation of the norm, and show its application to traffic simulation with the driving simulation software used at Renault, SCANER@II.

1 Introduction

Many multi-agent applications benefits greatly from the notion of normative systems. Such applications can exploit many characteristics of norms: they offer regulation possibilities, and can help to introduce coordination and cooperation improvements. The field of application has thus grown during the last years from law and virtual societies to disaster management or transport, and is still widening. However, works mainly concern normative system architectures [1], norm representations [2], norm adherence, or norm emergence among societies [3]. Less common are works on norms in simulation.

Norms are usually used to specify the ideal behavior of the agents within the system. Indeed, the autonomy left to the agents tends to deviate them from their ideal behavior. Normative systems provide an interesting regulation means: when the ideal behavior is considered as a norm, the objective is to try to make the agents comply with it. In Electronic Institutions [4–6] for example, the institution uses norms to manage the social interactions of the agents. Agents interact within the environment, and the institution provides authority and control instances designed to regulate agents' behavior regarding the norm.

Some works have used norm in the context of simulation of spatially situated agents by focusing on the regulation capabilities instead of the organizational structure. Bou et al. [7] study how traffic control strategies can be improved by extending Electronic Institutions with autonomic capabilities. In [8], the authors show how the introduction of non-normative behaviors improves the realism of microscopic traffic simulation. By allowing agents to break some of the formal rules of the road, norms are implicitly taken into account in the agents' decision model.

To improve the model realism, violations are sometimes allowed, or even encouraged. In such cases, the institution provides adapted sanctions to regulate agents' behavior. However, violations are usually not considered as a means for the environment to regulate the agents' population itself. We propose here to use the violations of the norm to create realistic agents' behaviors. By considering the normative system not as a regulation means of the agent's internal state – as part of its decision model –, but as an environment's regulation means of the agents' population, this system can be used with reactive as well as cognitive agents.

This paper is organized as follows. First, we present the context of our study: the simulation of spatially situated agents. Then we describe the institutional environment, and present our approach: modeling behavioral differentiation in simulations as violations of the norm. The application of this model to the driving simulation software used at Renault, SCANER@II, is then shown. Finally we present the conclusion and perspective of our work.

2 Context: Simulation of Spatially Situated Agents

2.1 The Need of Behavioral Variety

In this paper, we consider the application of normative systems in a specific context: the simulation of spatially situated agents. This kind of simulation includes in particular all simulations where individual characteristics result in different behaviors. This includes for example pedestrian simulations [9] and traffic simulations [10]. In such simulations, agents move around the environment: they need to be able to compute their positions and displacements. Besides, we consider here only microscopic simulation. The behavior of the agents may be observed continuously; we have to ensure that every action, every movement of the agent is realistic.

When we consider this context, the variety of behaviors met during the simulation is important to be able to observe realistic microscopic behaviors. Group phenomena can emerge from the microscopic interactions of the agents. These phenomena, observed in the real world, are for example the formation of lines in multidirectional pedestrians flows, or the regrouping effects caused by the sociability of individuals (people tend to approach a group rather than staying alone). If all the agents own the same set of characteristics and use the same models (decision, displacement models), these phenomena can emerge from the

simulation. However, the possibility to obtain individual behaviors, like people always staying alone or with small groups, is not intrinsically guaranteed without complementary mechanisms.

Obtaining a behavioral variety is crucial for the microscopic simulation's realism. To achieve this goal we have to provide the agents with different individual characteristics. For pedestrians it could be the size of the agents or the displacement model they use; for drivers the preferred safety time or the acceleration rate.

2.2 The Need of Behavioral Consistency

Another point is that we have to be able to control the consistency of agents' behaviors. Indeed, if the simulation produces inconsistent behaviors, the validity of the experimentation has to be reconsidered.

In most simulations, sets of parameters characterize agents' behaviors. Any set can be generated and used, but only some of them result in meaningful behaviors, and should be kept. For instance, let consider agents having only two behavioral parameters, p and q . If p can take n different values, and q m different ones, $n * m$ behaviors can be generated (Fig. 1). However, in many cases, the associated values will not produce a consistent behavior. Here p_1 associated to q_2 produces an inconsistent behavior, which has to be excluded from the simulation.

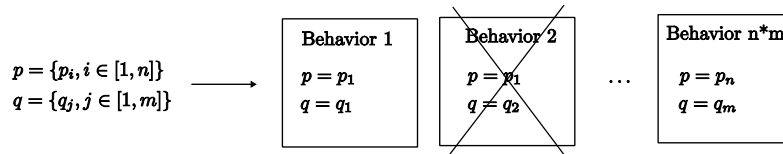


Fig. 1. Only some sets of parameters should be generated to produce consistent behaviors. A mechanism excluding inconsistent ones (behavior 2 for example) has to be provided.

In Figure 2, we illustrate this approach with a more specific example. We use two kind of drivers, cautious and aggressive, associated to only two parameters, safety time t and acceleration a . If we generate randomly each combination, we will obtain drivers using a high acceleration and a high security distance, and drivers using a low acceleration and a low security distance. These behavior are not realistic, and do not match any classification of real drivers. Moreover, in real cases the data used are continuous, and the environment laws and their interpretation by agents add a high complexity to the issue.

To be able to introduce accurately proportion of agents showing specific and consistent behaviors, we need to be able to use only specific sets of parameters, after having determined and quantified their validity.

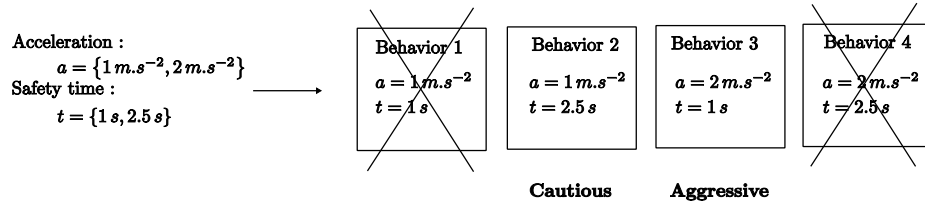


Fig. 2. A similar example using real parameters. Here we want to be able to keep only the sets of parameters matching meaningful behaviors (cautious and aggressive).

3 Institutional Environment

In most Electronic Institution systems norm violation is allowed, and sometimes promoted as a means to improve the institution’s mechanisms [8, 11]. In our case, norms are used to build and control the context of the simulation, and not as the decision model of the agents. We do not use here explicit authoring agents: norms are only used to create agents’ characteristics.

3.1 Semantic

We made the choice to use the same terminology as in classical normative approaches, but voluntarily did not used the terms in their common acceptance. We adapted the definitions to the context, as this redefinition allows us to describe efficiently the model used.

Institution. According to the choice we presented, the institution will not handle authority and controller agents. Its only role is to manage the norms in the environment. However, the institution may be related to a particular context, so we keep track of a set of institutional and environmental values handling these properties. The institution is mainly used as a set of parameters and definition domains. Parameter is used here with a wide meaning: it can be an action rule associated to its pre-conditions.

Definition 1. We define an Institution as a tuple $\langle P, D_P, P_i, P_e \rangle$ where:

- P is a finite set of parameters.
- $D_P = \{d_p, \forall p \in P\}$ is a set of definition domains, defined for each element in P .
- P_i is a set of institutional properties.
- P_e is a set of environmental properties.

Norm. Norms are defined as a subset of the institution parameters, associated to subsets of the definition domains. For instance, a norm can be described by a parameter and the distribution function describing the values it can take. They

handle specific sets of institutional and environmental properties, which can specialize institution's ones. Conflicting norms are allowed ; their preference ordering and their interpretation is left to the agents' decision model. At this step, enforcement strategies, like punishment, are not included. Several norms can be defined for the same environment, and norms can have non-empty intersections.

Definition 2. We define a Norm as a tuple $\langle I, P_n, D_{P_n}, P_{n_i}, P_{n_e} \rangle$ where:

- I is the institution the norm refers to.
- $P_n \subset P$ is the subset of parameters associated to the norm.
- $D_{P_n} \subset D_P$ is the subset of definition domains.
- P_{n_i} is a set of institutional properties.
- P_{n_e} is a set of environmental properties.

Behavior. A behavior describes the instantiation of a norm. Each element of the behavior is described by a parameter taken from the corresponding norm, and a value associated to this parameter. This value can be taken in or outside the definition domain associated to this parameter in the norm. Note that the definition domain can be a set of functions: the parameter's associated value will then be itself a function.

Definition 3. A Behavior is defined as a tuple $\langle N, P_b, V_{P_b}, P_{b_i}, P_{b_e} \rangle$ where :

- N is a reference to the instantiated norm.
- P_b is a subset of the set of parameters defined in the instantiated norm.
- V_{P_b} is the set of values associated to the parameters.
- P_{b_i} is a set of institutional properties.
- P_{b_e} is a set of environmental properties.

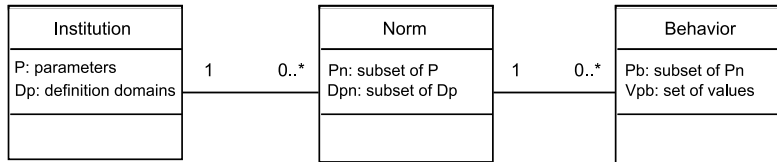


Fig. 3. The different elements of the institutional environment and their relationships.

3.2 Modeling Behavioral Differentiation as a Violation of the Norm

For each agent, a behavior is instantiated. This behavior defines the set of parameters and associated values used. The values are determined during the instantiation: they can either be in the definition domain defined by the norm, or

outside the domain. Depending on this instantiation, an agent will follow all or part of the whole set of norms defined by the institution.

Knowing the norm, we are able to establish which parameters are in their definition domain. If the value is in the definition domain, the parameter respects the norm. If not, it is a violation. This mechanism allows us to quantify the deviation from the norm: we know which parameters are in violation, and are able to determine the gap between the current value and the domain’s one.

Let consider drivers’ behavior regarding the safety distance on roads. In the Highway Code, only recommendations are provided: “allow at least a two-second gap between you and the vehicle in front on roads carrying faster-moving traffic and in tunnels where visibility is reduced” (rule 126 of the English Official Highway Code [12]). You can be fined for dangerous driving if you drive too close to the vehicle in front of you, but there is no obligation regarding this point. We define this as a norm, which can be expressed in different ways with our formalism (Tab. 1). Using the first possibility, a behavior which instantiate this norm can take the value t_s , and be part of the norm, or any other value $t = t_s + \delta$, $\delta \in [-t_s, +\infty]$ and be in violation. We are also able to quantify the deviation: if $t_s = 2\text{ s}$ and $\delta = 0.5\text{ s}$, a deviation of 25% is observed. This way, too deviant behaviors can be excluded. With the second possibility and $t_s = 2\text{ s}$, a value of 1.5s stays within the norm’s definition domain. These two norms illustrate how norms’ definition can provide different permissiveness levels.

Table 1. Two different ways to express the safety time norm.

	Parameter	Value
First possibility	safety time	t_s
Second possibility	safety time	Gaussian distribution with $\mu = t_s$ and $\sigma^2 = 0.25$

The data model describes the choice of agents’ behavioral parameters as instantiations of the norms. By allowing the selection of these parameters within the norm’s limits, or as deviations, we provide a flexible behavioral differentiation’s mechanism.

3.3 Random Parameters Generating the Behavioral Differentiation

This description allows us to manage the simulation using a nondeterministic mechanism: global parameters describe the randomization of the behavior of each agent. These parameters, which can themselves be randomly chosen, are used to generate every other randomized parameter.

The randomization level of the simulation can then be fixed. If it is defined at the simulation level, all below structures will be randomized using the higher-level factor. However, if we choose to preserve more control on the agents characteristics, we are able to define the factor for each of them (Fig. 4).

In addition, the degree of randomization of the simulation can also be set. The simulation can be either fully determined (simulation’s level parameter set to 1), or totally randomized (simulation’s level parameter set to 0).

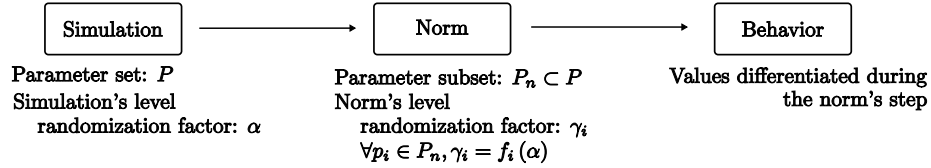


Fig. 4. The proposed randomization mechanism allowing to automatically generate a full set of behaviors.

4 Road Traffic Context

The normative system we place ourselves in is the road system. It is regulated by various elements: the Highway Code first, which provides sets of rules enforced by laws and sets of recommendations; and second the habits established by drivers during their daily use of their vehicles.

4.1 Describing the Traffic Law as a Set of Obligations and Norms

We are dealing here with a system designed to reproduce realistic human behaviors. In such a context, agents try 1. to respect the law and 2. to act within the norms of the environment. In [13] the authors present a distinction between the notion of obligation and the notion of norm: “in human societies, norms assist in standardizing the behavior of individuals, making it easier to cooperate and/or interact within that society. [...] Obligations, on the other hand, are associated with specific enforcement strategies which involve punishment of violators”. In our approach, we will use this distinction to characterize the prominence of law and norm related rules. Obligations have to be respected; others rules, including advices and local adaptation in different societies, constitute the norms.

We will not extensively describe traffic law, but present some of its specificities to illustrate our approach. Traffic laws can be described by the Tab. 2, completed by signals by authorized persons (police officers, school crossing patrol) and road markings.

The English Official Highway Code [12] explicitly presents a set of “must / must not” rules. They are associated to advices and recommendations, for which the code states that “although failure to comply with the other rules of the Code will not, in itself, cause a person to be prosecuted, The Highway Code may be used in evidence in any court proceedings under Traffic Acts to establish liability”. Even if these additional rules are not subjected to automatic punishment, they are explicitly provided to establish a framework for the normative system. Other codes, like the French one, present the same kind of characteristics.

Table 2. Main traffic laws categories, extracted from the Highway Code

Traffic laws	Road signs	Light signals
Speed limits	Regulatory signs	Traffic light signals
Right of way	Warning signs	Motorway signals
Passing	Direction signs	Lane control signals
Lane usage	Information signs	
Signaling	Road works signs	
Turning		

4.2 Environmental and Individual Factors

However, driving presents the particularity that many rules are subject to interpretation. For instance, a driver may be dangerous even if he does not break any rule. If aggressive drivers often do not respect some of the advices expressed in the Highway Code, cautious ones respect them. In addition, over-cautious drivers interfering with the traffic flow can endanger others road users.

The application of the rules is also influenced by environmental elements: differences exists from a country to another, and even from a town to another. For example, if you are a pedestrian in Germany and want to cross the road, drivers will consider you will wait for the traffic light signal and use the pedestrian way. They will be surprised if you do not, which can lead to dangerous situations. However, if you use the same behavior in Napoli, you will probably have to wait for a long time, as drivers consider you have to take the right of way.

Finally, several psychological factors are involved in driver's behavior [14]: personality, emotion, motivation and social behavior. Psychological based driver models have been developed [15], but the lack of links between measurable and psychological parameters makes their concrete application difficult. Besides those presented above, drivers take into account various rules encountered in the real world [16]:

- formal rules (rules of the road),
- informal rules (practices or conventions which can be in contradiction with the formal rules, like not yielding at crossroads or roundabouts),
- design of the road (which is often the origin of informal rules appearance),
- and other drivers behavior (their current behavior as well as the anticipated one).

Every drivers do not have the same rules sets: consistent aggressive, formal, informal and cautious groups emerge. The road let people expose their personality, and the emotional state can influence the behavior. This is why such multiplicity of behaviors can be observed, and has to be reproduced in simulations.

5 Application to Traffic Simulation

The application of this work is to be able to reproduce these kinds of behaviors in traffic simulation. We present in the next section the first steps of the application of our model in the driving simulation software used at Renault, SCANer@II³.

5.1 Driving Simulators and Traffic Simulation

Traffic simulation can be approached in several ways, depending on the requested level of detail. However, when dealing with a driving simulator, only a microscopic representation is suited: the vehicles evolving around the interactive one should have a convincing behavior, which macroscopic models cannot provide.

Driving simulators are used at Renault for different studies: ergonomics of the driver's cab, validation of embedded systems, comfort, design and validation of car lightings (Fig. 5)... This means that the environment has to be as realistic as possible, to allow the immersion of the users in the simulation and ensure results' validity.

Various traffic management models have been developed in the driving simulators field during the last fifteen years. They use different decision models to simulate drivers behavior [17–19]. However, behavioral differentiation is not considered as a specific issue in these applications. In macroscopic simulations, like AIMSUN [20], this kind of mechanism sometimes exists for traffic generation functions.

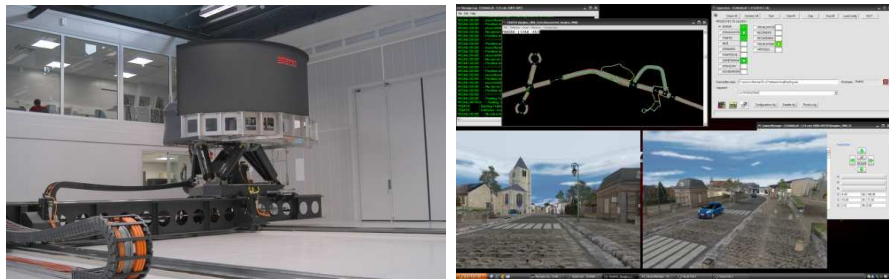


Fig. 5. The dynamic simulator Ultimate at Renault, and a screenshot of the SCANer@II software with two visuals outputs, the traffic and the supervisory modules.

5.2 Model's Parameters

In traffic simulation, agents' characteristics are usually described by a set of numerical data used in the decision model. Among them acceleration, braking,

³ SCANer@II has initially been developed by Renault, and is now distributed and co-developed by Oktal (<http://www.scaner2.com/>)

security distance, security margin, or even psychological factors like time to collision or time to lane crossing are typically used.

In SCANER@II, different pseudo-psychological parameters are taken into account by the decision model:

- overtaking risk parameter affects the automaton’s state transition,
- maximal speed and speed coefficient allow the vehicles to bypass speed limitations,
- safety time affects the following distance,
- observe signs and observe priority parameters are boolean rules regarding signalization.

However, once set, these parameters do not evolve, except through scenario rules. Values can be set without knowing the result and no consistency of the resulting behavior is guaranteed. Physical parameters are involved in traffic model computation (maximal speed, angle, acceleration, and braking), but external circumstances have no impact on their taking into account.

In this first step, we applied the model on the existing decision model’s input parameters. This led to the institution presented in Table 3.

Table 3. Institution with the existing parameters using the presented model.

Institution: $\langle RoadTraffic \rangle$	
$P = \{p_i, i \in [1, 6]\}$	$D_P = \{d_{p_i}, i \in [1, 6]\}$
$p_1 = \text{overtaking_risk}$	$d_{p_1} = [0, 1]$
$p_2 = \text{maximal_speed}$	$d_{p_2} = [0, +\infty]$
$p_3 = \text{speed_coefficient}$	$d_{p_3} = [0, +\infty]$
$p_4 = \text{safety_time}$	$d_{p_4} = [0, +\infty]$
$p_5 = \text{observe_signs}$	$d_{p_5} = \{true, false\}$
$p_6 = \text{observe_priority}$	$d_{p_6} = \{true, false\}$
$P_i = \{right_driving\}$	
$P_e = \{France, Italy\}$	

Using this institution, we are now able to define different norms. Two examples are presented below. The first one represents the norm “driving on a highway” (Tab. 4). All the parameters defined are used ($P_n = P$); the definition domains are restrictions of the institution’s ones. Drivers do not take risks to overtake, they drive within the speed limits, do not bypass them, and observe both priorities and signalization.

The second example represents the norm “aggressive driving on a highway” (Tab. 5): again all parameters are used, but the definition domains are adapted to reflect that aggressive driver take more risks, drive faster and use smaller security margins. The norm allows not respecting priorities or signalization.

With these norms, different behaviors can then be characterized. An example of aggressive driver is presented Table 6. Note that this instantiation do

Table 4. The norm describing driving on a highway using the institution defined above.

Norm: $\langle \text{HigwayDriving} \rangle$	
$I = \langle \text{RoadTraffic} \rangle$	
$P_n = \{p_{n_i}, i \in [1, 6]\}$	$DP_n = \{d_{p_{n_i}}, i \in [1, 6]\}$
$p_{n_1} = \text{overtaking_risk}$	$d_{p_{n_1}} = \{1\}$
$p_{n_2} = \text{maximal_speed}$	$d_{p_{n_2}} = [80, 130]$
$p_{n_3} = \text{speed_coefficient}$	$d_{p_{n_3}} = \{1\}$
$p_{n_4} = \text{safety_time}$	$d_{p_{n_4}} = [1.5, 2.5]$
$p_{n_5} = \text{observe_signs}$	$d_{p_{n_5}} = \{true\}$
$p_{n_6} = \text{observe_priority}$	$d_{p_{n_6}} = \{true\}$
$P_{n_i} = \{\text{right_driving}\}$	
$P_{n_e} = \{\text{France, highway}\}$	

Table 5. The norm describing aggressive driving on a highway using the institution defined above.

Norm: $\langle \text{HigwayAggressiveDriving} \rangle$	
$I = \langle \text{RoadTraffic} \rangle$	
$P_n = \{p_{n_i}, i \in [1, 6]\}$	$DP_n = \{d_{p_{n_i}}, i \in [1, 6]\}$
$p_{n_1} = \text{overtaking_risk}$	$d_{p_{n_1}} = [1.5, 3]$
$p_{n_2} = \text{maximal_speed}$	$d_{p_{n_2}} = [130, 160]$
$p_{n_3} = \text{speed_coefficient}$	$d_{p_{n_3}} = [1.5, 2]$
$p_{n_4} = \text{safety_time}$	$d_{p_{n_4}} = [0.2, 1]$
$p_{n_5} = \text{observe_signs}$	$d_{p_{n_5}} = \{true, false\}$
$p_{n_6} = \text{observe_priority}$	$d_{p_{n_6}} = \{true, false\}$
$P_{n_i} = \{\text{right_driving}\}$	
$P_{n_e} = \{\text{France, highway}\}$	

not violate the norm: every value is in the definition domain defined of the instantiated norm. If one of the value had been taken outside (for example if the maximal_speed value was 190), a violation would have been observed.

Table 6. An instantiation of the aggressive driving norm results in an aggressive behavior.

Behavior	
$N = \langle \text{HighwayAggressiveDriving} \rangle$	
$P_b = \{p_{b_i}, i \in [1, 6]\}$	$DP_b = \{d_{p_{b_i}}, i \in [1, 6]\}$
$p_{b_1} = \text{overtaking_risk}$	$v_{p_{b_1}} = 2$
$p_{b_2} = \text{maximal_speed}$	$v_{p_{b_2}} = 150 \text{ km/h}$
$p_{b_3} = \text{speed_coefficient}$	$v_{p_{b_3}} = 1.6$
$p_{b_4} = \text{safety_time}$	$v_{p_{b_4}} = 0.2 \text{ s}$
$p_{b_5} = \text{observe_signs}$	$v_{p_{b_5}} = \text{false}$
$p_{b_6} = \text{observe_priority}$	$v_{p_{b_6}} = \text{false}$
$P_{b_i} = \{\text{right_driving}\}$	
$P_{b_e} = \{\text{France, highway}\}$	

Finally, Figure 6 presents an example on the use of such aggressive behavior in the application. Using a similar norm as in Table 6, with a small safety time and no obedience to priority rules, vehicles are now able to take the right of way in intersections.

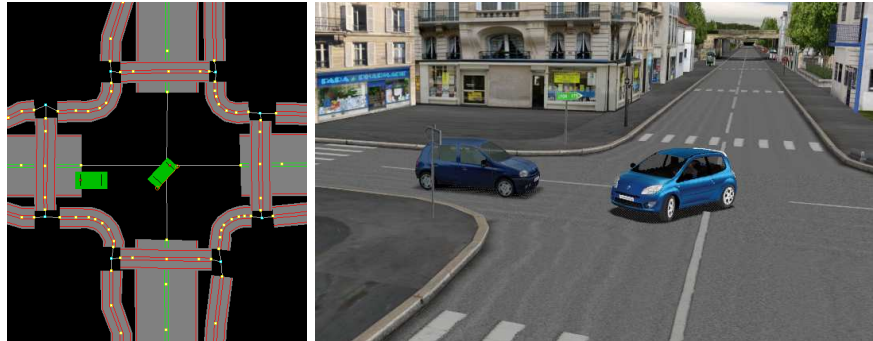


Fig. 6. 2D and 3D views of a vehicle using an aggressive behavior and taking the right of way in an intersection.

6 Conclusion and Perspectives

In this paper we have presented an approach to model behavioral differentiation as deviations from the norm in simulations of spatially situated agents. The institutional environment is composed of institution, norms and behaviors. The institution manages a set of parameters associated to their definition domains. The norms are subsets of these parameters and domains, and behaviors instantiations of the norm. The values of behaviors' parameters can be in or outside the definition domain provided by the norm. With this model, any kind of behavior can be generated, either matching or violating the defined norms. Such behavioral variety is needed in microscopic simulations, where behavioral differentiation is an important realism criterion. We are also able to quantify the deviance rate of these behaviors. Besides, a randomization mechanism can be added, to automatically create whole sets of behavior. Finally, this approach has been applied for traffic simulation, in the road traffic context. In this first step, the existing parameters have been used to generate various agents' behaviors.

The next steps of our work include the introduction of a more complete typology of real behaviors in the simulation, and the use of new parameters to improve the behavioral differentiation. We will then be able to study which sets of behaviors produce interesting macroscopic and microscopic results, and compare them with real behaviors. We will also introduce the possibility to modify dynamically the behavior of the agents during the simulation, in order to take into account changes in the environment or to simulate the evolution of agents' mental state.

References

1. Boella, G., van der Torre, L.: An architecture of a normative system: count-as conditionals, obligations and permissions. In: International Joint Conference AAMAS, New-York, USA (2006) 229–231
2. Boella, G., van der Torre, L.: Regulative and constitutive norms in normative multiagent systems. In: KR'04. (2004) 255–265
3. Savarimuthu, B., Cranefield, S., Purvis, M., Purvis, M.: Role model based mechanism for norm emergence in artificial agent societies. In: Workshop on Coordination, Organization, Institutions and Norms in Agent Systems (COIN), held with AAMAS'07, Honolulu, Hawaii, USA (2007) 1–12
4. Vázquez-Salceda, J., Dignum, V., Dignum, F.: Organizing multiagent systems. *Journal of Autonomous Agents and Multi-Agent Systems* **11** (2005) 307–360
5. Noriega, P.: Agent mediated auctions: The Fishmarket Metaphor. PhD thesis, Universitat Autònoma de Barcelona (1997)
6. Esteva, M., Padget, J., Sierra, C.: Formalizing a language for institutions and norms. In Meyer, J.J.C., Tambe, M., eds.: *Intelligent Agents VIII*. Volume 2333 of LNAI., Springer-Verlag (2001) 348–366
7. Bou, E., López-Sánchez, M., Rodríguez-Aguilar, J.A.: Adaptation of autonomic electronic institutions through norms and institutional agents. In: *Engineering Societies in the Agents World VII*. Volume 4457 of LNCS., Springer Verlag (2007) 300–319

8. Doniec, A., Espié, S., Mandiau, R., Piechowiak, S.: Non-normative behaviour in multi-agent system: Some experiments in traffic simulation. In: International Conference IAT, Hong Kong, China (2006) 30–36
9. Lacroix, B., Mathieu, P., Picault, S.: Time and space management in crowd simulations. In: European Simulation and Modelling Conference, Toulouse, France (2006)
10. Lacroix, B., Mathieu, P., Rouelle, V., Chaplier, J., Gallée, G., Kemeny, A.: Towards traffic generation with individual driver behavior model based vehicles. In: Driving Simulation Conference, Iowa City, USA (2007) 144–154
11. Castelfranchi, C., Dignum, F., Jonker, C., Treur, J.: Deliberative normative agents: Principles and architecture. In Jennings, N., Lesperance, Y., eds.: Agent Theories Architectures and Languages, Orlando, USA (1999) 206–220
12. for Tr. (Department for Transport), D.: The Official Highway Code 2007 Edition. The Stationery Office (2007)
13. Dignum, F., Morley, D., Sonenberg, L.S., Cavedon, L.: Towards socially sophisticated bdi agents. In: International Conference on MultiAgent Systems, Boston, USA (2000) 111–118
14. Dewar, R. In: Individual Differences. Human Factors in Traffic Safety (2002) 111–142
15. Keskinen, E., Hatakka, M., Laapotti, S., Katila, A., Peraaho, M. In: Driver Behaviour as a Hierarchical System. T. Rothengatter and R.D. Huguenin (2004)
16. Björklung, G., Aberg, L.: Driver behaviour in intersections: Formal and informal traffic rules. *Transportation Research Part F* **8** (2005) 239–253
17. Espié, S., Saad, F., Schnetzler, B., Bourlier, F., Djemane, N.: Microscopic traffic simulation and driver behaviour modelling: the ARCHISIM project. In: Road Safety in Europe and Strategic Highway Research Program (SHRP). (1994) 22–31
18. Wang, H., Kearney, J., Cremer, J., Willemsen, P.: Steering behaviors for autonomous vehicles in virtual environments. In: IEEE Virtual Reality Conference. (2005) 155–162
19. Olstam, J.: Simulation of rural road traffic for driving simulators. In: Transportation Research Board, Washigton D.C., USA (2005)
20. Barcelo, J., Casas, J.: Dynamic network simulation with AIMSUN. In: International Symposium on Transport Simulation, Yokohama (2002)