The Use of Norms Violations to Model Agents Behavioral Variety

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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 the simulation of spatially situated agents, typically moving around simulated physical environments. Our goal is to provide a mechanism allowing an efficient generation of consistent agents characteristics. We propose to model behavioral differentiation as violations of the norms, and show its application to traffic simulation with the driving simulation software used at Renault, SCANeR™.

1 Introduction

Many multi-agent applications benefit 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 move them away from their ideal behavior. Normative systems provide an interesting regulation means: when the ideal behavior is considered as a norm, the objective is to make the agents comply with it. In Electronic Institutions [4,5,6] for instance, the institution uses norms to manage the social interactions of the agents. They interact within the environment, and the institution provides authority and control instances designed to regulate their behavior.

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Some works have used norm in the context of simulation of spatially situated agents by focusing on the regulation capabilities, and not on the organizational structure. Bou et al. [7] study how traffic control strategies are improved by extending Electronic Institutions with autonomic capabilities. Depending on traffic events, the institution optimizes its response, like the fines amount. 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 rules of the road, norms are implicitly taken into account in the decision model.

To improve the realism of the model, violations are sometimes allowed, or even encouraged [9]. In such cases, the institution provides adapted sanctions to regulate agents behavior. We propose in this paper to describe the behaviors using norms, and to use violations to efficiently create realistic and diversified behaviors. The normative system is thus not considered as a regulation means of the agents internal state – as part of their decision model –, but as an environment's regulation means of the agents population.

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 norms violations. Finally, the application of the model to the driving simulation software used at Renault, SCANeR™, is shown, and experimental results demonstrating the interest of the approach are presented.

2 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 all simulations where individual characteristics result in different behaviors, like for instance pedestrian simulations [10] or traffic simulations [11]. 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. Agents behavior may be observed continuously, and we have to ensure that each of their actions is realistic.

In this context, the variety of behaviors is important to be able to observe realistic situations during the simulation. Indeed, group phenomena can emerge from the microscopic interactions of the agents. These phenomena, observed in the real world, are for instance 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). Even if all the agents own the same set of characteristics and use the same models (decision, displacement models), these phenomena might be observed in the simulation. However, the possibility to obtain individual behaviors, like people staying alone or with small groups, is not intrinsically guaranteed without complementary mechanisms.

Creating a behavioral variety is crucial for the 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 desired speed or the safety time.

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 ones when it is designed to reproduce real world situations, 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: only those should be kept (Fig. 1). In Figure 2, a more specific example is presented. We suppose that drivers are characterized by two parameters, acceleration a and safety time t, which can be picked out from continuous predefined intervals. When generating randomly combinations of these parameters, drivers using a high acceleration and a low safety time are created, as well as drivers using a low acceleration and a high safety time. They can naturally be classified as aggressive and cautious, matching usual classifications of real drivers. However, other associations are also produced: drivers using high acceleration and safety time, or low ones. The behaviors resulting from these parameters are not realistic, and a mechanism has to be provided to exclude them.

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 and to quantify their validity.

2.3 Towards a Normative Model

The description capabilities of norms offer various assets to achieve the different goals presented above. Indeed, they provide different means to create the variety

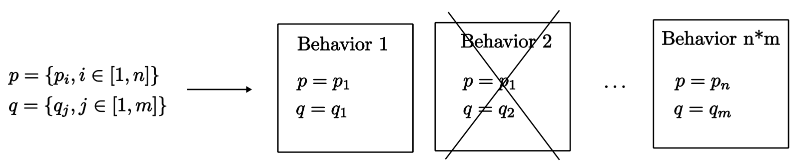

Fig. 1. Only some sets of parameters should be generated to produce consistent behaviors. A mechanism excluding inconsistent ones (like behavior 2) has to be provided.

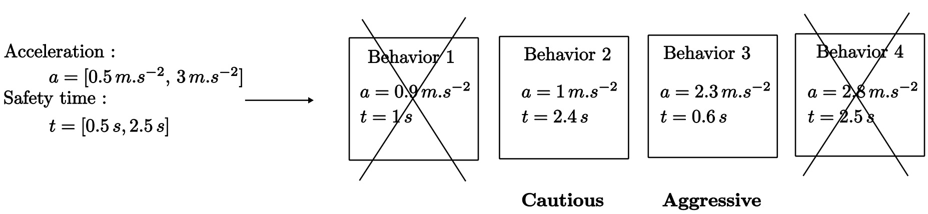

Fig. 2. A similar example using real parameters. The only sets of parameters we want to keep have to match meaningful behaviors.

we are looking for. The first possibility is to exploit the definitions of the norms themselves. They can be used as generic structures allowing describing any kind of behavior: a wide variety of norms may coexist, using various parameters. The second possibility is to allow violations of the defined norms, which can produce interesting new and unexpected behaviors. As for the consistency, the generation of the behaviors within the norms limits guarantees it. If violations are allowed, the deviations have to be quantified to remain in predefined limits.

Finally, when dealing with simulation of spatially situated agents, the goal is often to reproduce existing behaviors. The intuitive description of the world provided by norms allows users and scenario designers to easily comprehend the generation mechanism, which they can then configure and modify by themselves.

3 Institutional Environment

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 structures: 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. The definitions are adapted to the context, as this redefinition allows describing efficiently the model.

Institution. According to the choice we presented, the institution does not handle authority and controller agents. Its role is to manage the norms in the environment. However, the institution may be related to a particular context, so we keep track of sets of institutional and environmental properties. The institutional properties refer to criteria regarding law and obligations, environmental ones are related to contextual elements. 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.*
- 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. Norms handle specific sets of institutional and environmental properties, which can specialize institution 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* $\left\langle I, P_n, D_{n_{P_n}}, P_{n_i}, P_{n_e} \right\rangle$ *where:*

- I *is the institution the norm refers to.*
- $P_n \subset P$ *is the subset of parameters associated to the norm.*
- $D_{n_{P_n}} \subset D_P$ *is the subset of definition domains:*
  $\forall p_n \in P_n$, $\exists p \in P$, $p_n = p$, $d_{n_{p_n}} \subset d_p$
- 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* $\langle N, P_b, V_{P_b} \rangle$ *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.*

A detailed example using these definitions is presented in Section 4.4.

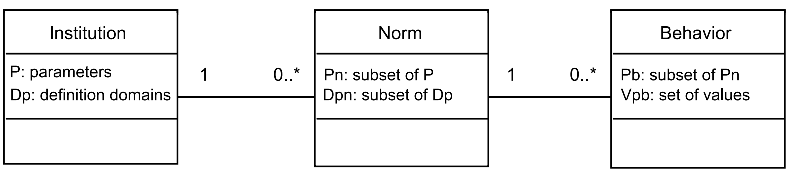

Fig. 3. The different elements of the institutional environment and their relationships

3.2 Behavioral Variety as Violation of the Norm

The violation of the norms offers possibilities to increase the behavioral variety. For each agent, a behavior is instantiated. The set of parameters and associated values is determined during the instantiation: they can either be in the definition domain defined by the norm, or outside. If the value is in the definition domain, the parameter respects the norm. If not, it is a violation. The norm being known, we are able to establish which parameters are in their definition domain, and to determine the gap between the current value and its domain. This characteristic allows quantifying the deviation from the norm. Two criteria

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

	safety time definition domain
first expression	singleton, t_s
2nd expression	normal distribution, $\mu = t_s$, $\sigma^2 = 0.25$

can be used: firstly, the number of values of the behavior's parameters outside the limits defined in the norm; secondly, the gap between a generated value and its original specification.

For instance, consider the behavior of drivers 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 (Table 1). Using the first expression, a behavior which instantiates this norm can take the value t_s, and belong to the norm. If it takes any other value $t = t_s + \delta$, $\delta \in [-t_s, +\infty]$ we observe a violation. We are also able to quantify the deviation: if $t_s = 2\,\mathrm{s}$ and $\delta = 0.5\,\mathrm{s}$, a deviation of 25 % is observed. This way, too deviant behaviors can be excluded. With the second expression, if $t_s = 2\,\mathrm{s}$, a value of 1.5 s stays within the domain: no violation is observed. These two norms illustrate how norms definition can provide different permissiveness levels.

This quantification can be used to fulfill various needs. It allows us to exclude too deviant behaviors, as we are able to quantify the deviance and set limits on the potential gaps. It can also be used to create unexpected behaviors, even aberrant ones, and study their influence on the simulations.

3.3 Generating Behavioral Variety

The simulation is managed using a nondeterministic mechanism: global parameters describe the randomization of agents behavior. These parameters are used to generate every other randomized parameter in the simulation, and can themselves be randomly chosen.

With this mechanism, the randomization level of the simulation can be set. If it is defined at the simulation level, all structures are randomized using the

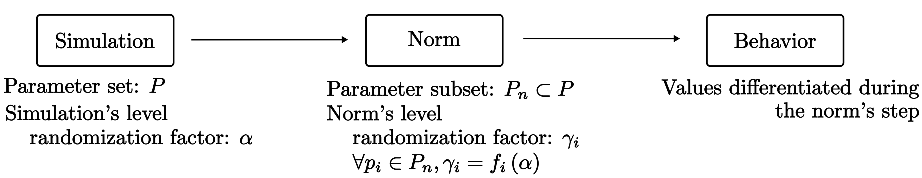

Fig. 4. Randomization mechanism allowing generating the behaviors

higher-level factor. However, if we decide to preserve more control on the agents characteristics, a different factor can be defined for each of them (Fig. 4). In addition, the degree of randomization of the simulation can also be chosen. The simulation can be either fully determined, with a simulation's level parameter set to 1, or totally randomized, with a simulation's level parameter set to 0. This generation mechanism is further detailed in [13].

4 Application to Traffic Simulation

One of the applications of this work is to reproduce various 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™[1].

4.1 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 driving 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, validation of car lightings (Fig. 5)... The environment has thus 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 [14,15,16]. However, behavioral differentiation is not considered as a specific issue in these applications. In macroscopic simulations, this kind of mechanism sometimes exists for traffic generation functions [17].

Fig. 5. The dynamic simulator Ultimate at Renault *(left)*, and a screenshot of the SCANeR™ software with two visuals outputs, the traffic and the supervisory modules *(right)*

[1] SCANeR™ has initially been developed by Renault, and is now distributed and co-developed by Oktal (http://www.scaner2.com/).

4.2 Road Traffic Context

The normative system we place ourselves in is the road system. Various elements regulate it: 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.

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.

As for individual elements, several psychological factors are involved in drivers behavior [18]: personality, emotion, motivation and social behavior. Psychological based driver models have been developed [19], but the lack of links between measurable and psychological parameters makes their concrete application difficult. Indeed, drivers take into account various rules encountered in the real world [20]:

– 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).

Driving presents several particularities: many rules are subject to interpretation, the road environment let people expose their personality, and the emotional state can influence the behavior. For instance, a driver may be dangerous even if he does not break any rule: over-cautious drivers interfering with the traffic flow can endanger others road users. The application of the rules can even differ from a country to another, or from a town to another, adding a dependence on environmental factors. A wide multiplicity of behaviors can be observed, which has to be reproduced in simulations to ensure the immersion of human drivers in the simulations.

4.3 Parameters of the Traffic Model

In traffic simulation, the individual characteristics of the agents are usually described by a set of numerical data used in the decision model. Among them acceleration, braking, security distance, security margin, or even psychological factors like time to collision or time to lane crossing are typically used.

In SCANeR™, the autonomous vehicles use a decision model based on a perception-decision-action architecture [11]. During the perception step, the driver identifies the elements it may interact with. It includes the roads, the road signs, the other vehicles and the pedestrians. The decision step is built on three levels. First, a strategic level plans the itinerary. Then, a tactical level is applied to select the next maneuver to be executed: drive on, overtake, change lane, or stop. This step uses a finite state automaton, which transitions are sensible to different parameters. After the maneuver's choice, an operational level computes the resulting acceleration and wheel angles. Finally, the action model computes the next position, using a dynamic model of the vehicle.

Six different pseudo-psychological parameters are taken into account in this decision model:

- maximal speed: the maximal speed a driver will adopt,
- safety time: the security distance it will use, depending on its speed,
- overtaking risk: the risks a driver will accept to overtake, function of the available gaps with oncoming vehicles,
- speed limit risk: a factor allowing bypassing speed limits,
- observe priority and observe signs: boolean parameters regarding the respect of signalization and priorities.

Their values can be set without any consistency check, and no consistency of the resulting behavior is guaranteed.

4.4 Implementation

We chose in this work to apply the proposed differentiation model on the existing pseudo-psychological parameters. Indeed, they influence the behaviors of the drivers, and represent adapted inputs in the traffic model. This led to the institution whose parameters and associated values are presented in Table 2. For the purpose of our example, the institutional and environmental properties are defined as follows: we consider the institution is valid in right driving countries ($P_i = \{right\_driving\}$), and only in France and Italy ($P_e = \{France,\ Italy\}$).

Different norms can then be defined in the context of this institution. Two examples are presented in Table 3: normal and aggressive driving on highways. The norm *normal highway driving* uses all the parameters defined in the institution ($P_n = P$), the definition domains are restrictions of the institution ones. A driver applying this norm does not take risks to overtake, drive within the speed limits, do not bypass them, and observe both priorities and signalization. The second example represents the norm *aggressive highway driving*: again all parameters are used, but the definition domains are

Table 2. Institution with the existing parameters using the presented model

$P = \{p_i, i \in [1, 6]\}$	$D_P = \{d_{p_i}, i \in [1, 6]\}$
p_1 = maximal_speed	$d_{p_1} = [0, +\infty]$
p_2 = safety_time	$d_{p_2} = [0, +\infty]$
p_3 = overtaking_risk	$d_{p_3} = [0, 1]$
p_4 = speed_limit_risk	$d_{p_4} = [0, +\infty]$
p_5 = observe_signs	$d_{p_5} = \{true, false\}$
p_6 = observe_priority	$d_{p_6} = \{true, false\}$

Table 3. Norms describing normal and aggressive driving on a highway

	normal highway driving	aggressive highway driving
p_{n_1} = maximal_speed	$d_{p_{n_1}} = [100, 140]$	$d_{p_{a_1}} = [140, 160]$
p_{n_2} = safety_time	$d_{p_{n_2}} = [0.8, 5.0]$	$d_{p_{a_2}} = [0.1, 1.2]$
p_{n_3} = overtaking_risk	$d_{p_{n_3}} = [-0.5, 0.5]$	$d_{p_{a_3}} = [1.0, 2.0]$
p_{n_4} = speed_limit_risk	$d_{p_{n_4}} = [0.0, 1.0]$	$d_{p_{a_4}} = [1.0, 10.0]$
p_{n_5} = observe_signs	$d_{p_{n_5}} = \{true\}$	$d_{p_{a_5}} = \{true, false\}$
p_{n_6} = observe_priority	$d_{p_{n_6}} = \{true\}$	$d_{p_{a_6}} = \{true, false\}$

Table 4. A normal and a violating instantiation of the *aggressive highway driving* norm. Only one parameter, the *maximal speed*, is in violation.

	aggressive driver	violating aggressive driver
p_{b_1} = maximal_speed	$v_{p_{b_1}} = 150\,\text{km/h}$	$v_{p_{b_1}} = 210\,\text{km/h}$
p_{b_2} = safety_time	$v_{p_{b_2}} = 0.2\,\text{s}$	$v_{p_{b_2}} = 0.3\,\text{s}$
p_{b_3} = overtaking_risk	$v_{p_{b_3}} = 2.0$	$v_{p_{b_3}} = 1.8$
p_{b_4} = speed_limit_risk	$v_{p_{b_4}} = 1.6$	$v_{p_{b_4}} = 3.0$
p_{b_5} = observe_signs	$v_{p_{b_5}} = false$	$v_{p_{b_5}} = true$
p_{b_6} = observe_priority	$v_{p_{b_6}} = false$	$v_{p_{b_6}} = false$

adapted to reflect that aggressive driver take more risks, drive faster and use smaller security margins. The norm allows not respecting priorities or signalization. As for the properties sets, the institutional one remains unchanged, but the environmental properties now include a parameter to restrict its use to highways only, and to France only: $P_{norm_i} = P_{aggr_i} = \{right\_driving\}$ and $P_{norm_e} = P_{aggr_e} = \{France,\ highway\}$.

These norms allow generating various behaviors. In Table 4, two instantiation of the *aggressive highway driving* norm are presented. The first one does not violate the norm: every value remains in the definition domain defined by the norm. A driver using these parameters in the traffic model presents a consistent behavior, while showing aggressive characteristics, like following closely the vehicles in front of it. The second instantiation represents the kind of behavior that may be created when violations are allowed. Here, only one parameter has been generated outside the norms, the *maximal speed*. The generated value leads to a coherent behavior, but if the value had led to an inconsistent behavior (for instance 400 km/h), the behavior should have been excluded.

4.5 Experimental Results

To evaluate the improvements brought by the introduction of the normative model, simulations using different sets of norms were realized.

A database representing an 11 km long section of highway was used (Fig. 6). The vehicles were created at the beginning of the section, using a traffic demand of 3800 veh/h (1900 veh/h per lane on both lanes). The recording of traffic data

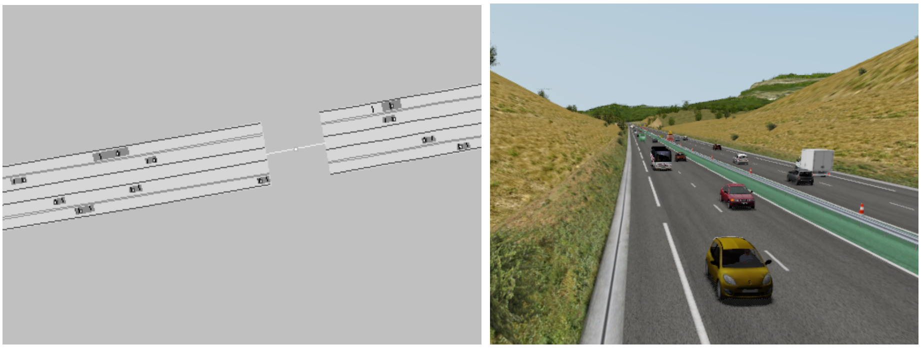

Fig. 6. 2D and 3D views of the highway database used for the experiment

was done using three detector placed on the highway, at kilometer 2.2, 6 and 10.8. The vehicles were created using the normative model, and the traffic model of the application then handled them during the simulation process. Three different sets of norms were used:

- no norms: all the vehicles are created with the same parameters,
- normal driver only: one norm is used, *normal highway driving*. Only one parameter is specified in the norm, the maximal speed. Its definition domain is a normal distribution of mean $\mu = 125$ and standard deviation $\sigma = 10$, truncated at 100 and 140 km/h,
- all norms: three norms are used, *cautious highway driving*, *normal highway driving* and *aggressive highway driving*. Each norm is defined with four parameters, which definition domains are truncated normal distributions. The values used are presented in table 5. The vehicles are created with the following proportions: 10 % cautious, 80 % normal, and 10 % aggressive.

Table 5. Cautious, normal and aggressive norms parameters

parameter	cautious	normal	aggressive
maximal speed	$[90, 125]$	$[100, 140]$	$[140, 160]$
	$\mu = 115$	$\mu = 125$	$\mu = 150$
	$\sigma = 10$	$\sigma = 10$	$\sigma = 5$
safety time	$[1.5, 5.0]$	$[0.8, 5.0]$	$[0.1, 1.2]$
	$\mu = 2.0$	$\mu = 1.5$	$\mu = 0.8$
	$\sigma = 0.5$	$\sigma = 0.5$	$\sigma = 0.4$
overtaking risk	$[-0.5, 0.5]$	$[-0.5, 0.5]$	$[1.0, 2.0]$
	$\mu = 0.0$	$\mu = 0.0$	$\mu = 1.5$
	$\sigma = 0.25$	$\sigma = 0.25$	$\sigma = 0.5$
speed limit risk	$[0.0, 1.1]$	$[0.0, 1.1]$	$[1.0, 10.0]$
	$\mu = 1.0$	$\mu = 1.0$	$\mu = 1.5$
	$\sigma = 0.05$	$\sigma = 0.05$	$\sigma = 0.25$

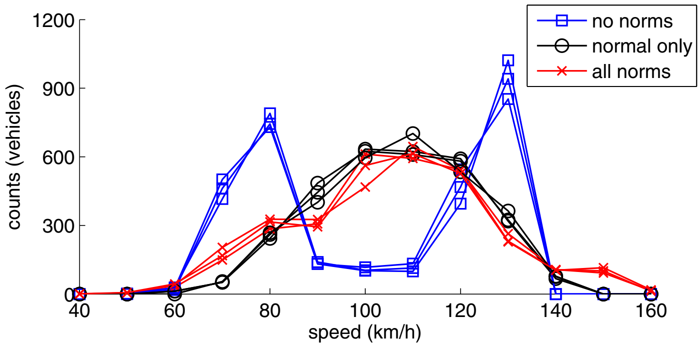

Fig. 7. Distribution of vehicles speeds at kilometer 6

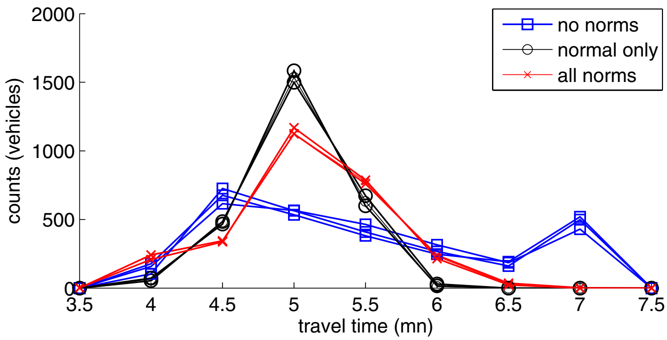

Fig. 8. Total travel time on the database

For each set of norms, the data obtained during three different runs are presented (Figs. 7 and 8), the duration of each simulation being one hour. The Figure 7 represents the distribution of vehicles speeds at the kilometer 6 (second detector). The first case, where no norm is used, shows a concentration of the speeds in two main areas: between 70 and 90 km/h for 46 % of the vehicles, and around 130 km/h for 40 % of them. This distribution is explained by the parameters similarity: vehicles are not able to take advantage of the traffic flow variations, which results in a slow right lane and a fast left one with few lane changes. In the second case, with one norm, 60 % of the vehicles speeds are between 90 and 115 km/h, and 30 % between 115 and 140 km/h. The resulting distribution is more balanced, but the average speed remains quite low, at 100.4 km/h. The last case, with three norms, presents a wider distribution of the speeds, and a slightly increased average speed (103.7 km/h).

The total travel time for each vehicle is presented in Figure 8, and provides interesting complementary results. As for the speeds, the use of norms produces more balanced distributions of results. In addition, the distributions widen when the number of used norms increases: a higher variety of behaviors results in more differentiated travel times. When studying the average travel times of the vehicles

Table 6. Average travel times

	avg travel time	evolution
no norm	5 mn 35 s	+13.2 %
normal only	4 mn 56 s	ref.
all norms	5 mn 14 s	+6.0 %

through the whole section (Table 6), we can also note that even if the average speed increases slightly when using more norms (+3.3 %), the travel time do not decrease, but increase (+6 %). The variety of behaviors explains again this result: more speeding vehicles are present, but the dynamicity of the traffic limits their progression.

However, different elements concerning the experiment have to be discussed. First, the norms choice, and the values used in the norms. The norms were chosen to reflect classifications defined in driving psychology. They may change to include more variety, or according to the population studied. As for the values used, they have been chosen empirically. An important improvement would be using calibration with real data, which is currently under work.

Second, the use of statistical data hides some of the characteristics of the traffic. Even if some properties appear, the visual observation of the traffic flows shows other particularities: increasing the variety increases highly the variety of individual behaviors in the traffic (overtakings, speed choices...). These results do not appear in the measured data, and we need to introduce new indicators allowing illustrating and quantifying these elements.

Finally, the possibility to generate violating behaviors was not exploited in these simulations. Even when creating aggressive drivers, we remained in the limits of the corresponding norm. This point will be introduced in further experiments, to simulate for instance erratic behaviors in the traffic.

5 Conclusion

In this paper we have presented an approach to model behavioral differentiation as deviations from the norm in simulations of spatially situated agents. Such behavioral variety is needed in microscopic simulations, where it is an important realism criterion. The institutional environment is composed of an 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 are instantiations of a 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 specified norms. We are also able to quantify the deviance rate of these behaviors. Finally, this approach has been applied to traffic simulation. In this first step, the existing parameters of the traffic model have been used to generate various agents behaviors. Statistical experimental results showed that the introduction of different norms improves the behavioral variety in the simulation, while allowing controlling the consistency of the behaviors.

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