A qualitative model for the simulation of traffic behaviours in a multi-lane environment[1]

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Abstract. Qualitative modelling of spatial relationships has often been considered as a context independent task in order to provide a reasoning model in generic form. Despite the significant interest in these models, there is still sufficient scope for context dependent reasoning in space and time. This paper proposes a qualitative spatial reasoning model, oriented to the modelling and simulation of several cars acting in a multi-lane circuit, which can be considered as an illustrative example of a constrained frame of reference. The modelling objects of interest are individual cars whose cardinal relationships to external cars and actions are modelled. This dynamic system is analysed, and a set of interrelationships is identified at different levels of abstraction, together with inference rules that model the displacement of several cars in a circuit. The potential of this model is illustrated and calibrated using an agent-based prototype.

Keywords: Spatial reasoning, Cardinal relationships, Simulation, Agent-based modeling.

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1. Introduction

Decentralized modeling has opened a new scientific approach for studying “emergent” phenomena, i.e., complex patterns emerging from interactions among simple components. The tendency to assume centralized control makes it difficult for people to understand many phenomena in the world (Resnick 1997). This deep-seated resistance to decentralised thinking is due to the habit of using since childhood the Newtonian way of thinking, focusing on the behaviours of systems, not on the actions of components. While the Newtonian approach of a system used macro-models able to reproduce the observable behaviour of a system, decentralized thinking has introduced the theory of micro-simulation. This is a bottom-up approach, where a complex system is viewed as a large set of small, interacting components. The method consists in constructing minimal microscopic models that are capable of reproducing the macroscopic laws of the system by emulating the behaviour of every individual entity in the system.

Decentralization signifies self-organization of systems. Its first principle is to establish simple rules for individual units. One must choose the most significant characteristics of the basic components of the system which will render a macroscopic behaviour, closest to reality as possible. This is usually difficult due to the enormous number of degrees of freedom a system can contain microscopically. The second principle is the use of cellular automata, a discrete spatio-temporal approach of microscopic units (Von Neumann 1966). In the concept of cellular automata, a virtual world is divided into a uniform grid of “cells” in which cellular automata move at each “step”, i.e., at each discrete unit of time. The essential features of a given cellular automaton are:

- its *state*, which is an array of parameters function of time or not,
- its neighborhood, defined by the presence or not of other cellular automata in the nearest cells,

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- its behavior, that is the set of rules that define its evolution at each time step. These rules are generally derived from its current state and neighborhood.

Cellular automata support the decomposition of complex behaviours much simpler individual units. By building appropriate rules into a cellular automaton, one can simulate many kinds of complex behaviours. Cellular automata favour simplified knowledge acquisition and increased computational performance. Related to cellular automata are agent-based systems in which autonomous agents react in their environment using some similar modelling principles. Agent-based simulations have provided a new approach for the simulation of complex physical systems which include many independent variables acting and reacting together (Casti, 1997). An agent-based system can be roughly defined as a computer-based virtual system with multiple agents acting within it. All agents have an ability to sense the environment they are "living on" and make actions based on what they perceive. In terms of degree of autonomy, such systems can be classified in different categories from reactive and non-autonomous agents to intelligent and highly autonomous agents. Reactive agents are only subject to local interaction and communication with their neighbouring agents and environment. Therefore, their actions are local rather than global. The global sense of the environment is given to the observer that interacts with the simulation and defines the initial conditions for the simulation according to his knowledge and previous experience of the system behaviour.

In order to replicate complex behaviours there is still a need to integrate some qualitative knowledge in the way autonomous agents react in their environment. For instance, multi-agent systems used to model dynamic systems consider some general modelling patterns at the individual level without considering different levels of abstraction in the way these agents perceive their environment. In traffic modelling, making a qualitative difference between driver behaviours is a very much relevant assumption as these drivers act differently in function of many physical and social parameters. The objective of this paper is to integrate qualitative modelling concepts within a combined multi-agent and cellular automata approach to replicate the behaviour of a multi-lane traffic system. We propose a spatial qualitative approach that gives several levels of abstraction in analysing the neighbourhood of individual vehicles acting in a circuit of reference. The model is illustrated and calibrated through a prototype development based on the agent-based software *StarLogo* developed by the MIT media Lab. (Resnick 1997).

The remainder of this paper is organised as follows. Section 2 briefly introduces traffic modelling principles. Section 3 introduces the basis for our modelling approach, and qualitative relationships between several dynamic vehicles within a circuit. These relationships are identified at different levels of abstraction. Section 4 proposes some inference rules that constitute the dynamics of the represented traffic system. The simulated system is presented, calibrated and discussed in Section 5. Finally Section 6 draws some conclusions.

2. Traffic modelling background

The development of traffic simulation since the early 1950's has been tremendous. This, of course, is partly due to the development of computer technology. Indeed, with the increasing speed and computational power of information technologies, traffic simulations have evolved from the fairly well covered local roads, to network wide systems where several types of units are integrated in one system. Computational implementations of traffic simulations are either based on continuous models of space and a discrete approximation of time based for example on differential equations (Wiedeman, 1997), or discrete representation of space and time based on autonomous decentralized systems, i.e., micro-simulation and cellular automaton (Cremer and Ludwig 1986, Simon and Nagel 1998). Decentralized simulations are based on the simulation of vehicle-vehicle interactions, so-called microscopic interactions. These vehicle interactions are modeled using some basic primitives :

- the agents, the actors of the simulation, that is the vehicles,
- the environment, the space in which the agents evolve, that is the road network, and

- the rules that determine the vehicle behaviours.

In a traffic simulation, rules can be identified around three main principles. The first one, so-called "forward motion" defines the way cars advance by accelerating and decelerating. The second one that defines the "lane changing rules", relies on two main criteria: (1) the *incentive criterion* : the need or not to change lanes in order to reach one's maximum speed faster and optimize one's travel time ; and (2) the *security criterion* : the possibility to change lanes if there is enough space in the target lane. One can also make a difference between symmetric (rules used by Americans) and asymmetric systems (rules mostly used by Europeans). In the symmetric system, a vehicle in the central lane can overtake by the right or by the left, all lanes are equivalent in terms of speed average. Whereas in the asymmetric system, a vehicle has to keep right, using the center and the left lanes only when it needs to overtake (the contrary in UK-based systems). In a traffic simulation, a vehicle perceives its environment within a given circuit through cardinal relationships and relative speeds: other cars are taken into account or not in function of their relative positions and relative speed. According to the importance given to individual driver behaviors, there are several levels of granularity, i.e. the way the agents "see" their world. Likewise, the perception of the world can also depend on the intelligibility of the agent.

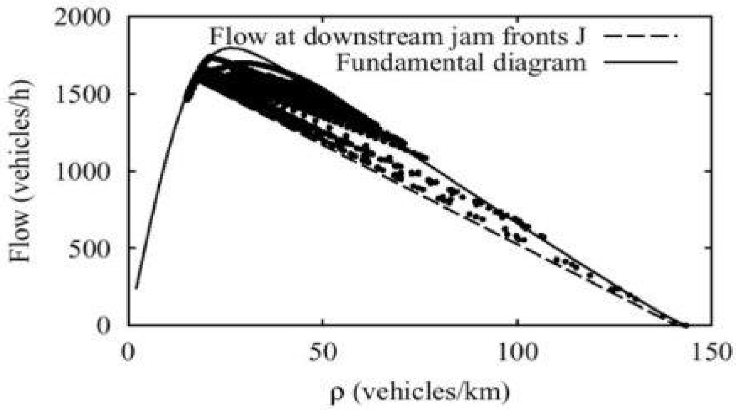


Figure 1 Flow-density graph

Modelling multi-lane traffic is not straightforward as the overall behaviour of such system is based on individual human decisions which are non-deterministic. Most simulation approaches attempt to replicate multi-lane traffic systems using microscopic models that replicate the observed behaviour of the macroscopic dynamic from vehicle actions identified at the individual level (Nagel *et al.* 1997). Current modelling approaches of multi-lane traffic are based on the modelling of a set of driving decision rules at the individual level, together with a computational model that simulates the evolution of a multi-lane system at the macro-level. These decision rules mainly model change of lanes decisions. These decision are based on several factors that can be summarised as follow: a vehicle changes lane if there is another vehicle ahead with a slower speed and if there is enough space ahead and behind to make this change of lane possible; The "ahead" factor is analysed with different approximations. Scheduling conflicts are also generally considered by simple algorithms that make either changes to a left lane or right lane the priority when a conflict does occur. The same method can be also applied to left and/or right lanes depending on national contexts and particularities. These approaches are generally calibrated and validated using the typical density inversion phenomena that mainly represents the fact that traffic flow increases nearly linearly with density until it reaches a maximum at 40 vehicles/km/2 lanes, from there traffic flow then decreasing with increasing density (see figure 1).

Individual displacement rules generate patterns at the global circuit level. Density is the main parameter in a traffic simulation. It defines the number of vehicles per km per lane. In every freeway traffic model, another quantity of interest is the average flow. A characteristic of a density versus flow graph in a traffic simulation is *traffic flow breakdown*.

As shown in Figure 1, traffic flow first increases nearly linearly with density until it reaches a maximum at the *traffic flow breakdown point*. From there flow decreases with increasing density, and the scatter of the values is much larger than before. The best explanation for this is that, for low densities, traffic is roughly laminar and jams are short lived. In consequence the addition of vehicles does not change the average speed much and flow is linear function of density. For high densities, traffic is an irregular composition of jam waves, and laminar outflow traffic between jams (Nagel *et al.* 1998).

Another pattern of a freeway traffic, which is specific to the asymmetric system, is the *density inversion* of lanes, i.e., if the flow is high enough, the passing lanes become more crowded than the one for slower cars. The equilibrium is only reached at densities above the *traffic flow breakdown point*, hence in traffic congestion. A new trend in traffic simulation is to analyze "stop-and-go waves", i.e., from free traffic downstream to synchronized congested traffic, in order to explain the origin of the phenomenon and to describe the detailed features of transition of stop-and-go patterns.

As the laws of interactions are based on human reaction, which are neither simple nor mechanical by nature, the first role of emerging data is to help the creator of the traffic simulation to calibrate his simulation. The parameters used to calibrate must run at a microscopic level. For instance, modifying the ratio between acceleration and deceleration has a strong influence on the occurrence of jams. Moreover, *security criteria* can be changed in a function of lanes in order to be closer to reality. The way people accelerate is a difficult pattern to model, e.g., people in a traffic jam tend to be less inclined to gain speed rapidly. In order to obtain a graphic with a significant *traffic flow breakdown*, there is a need to differentiate acceleration in a traffic jam and acceleration in a "free flow zone" (Kraub *et al.* 1998). A driver changes lanes for two reasons: because he wants to and because he can. Those two criteria are respectively the *incentive criterion* and the *security criterion.* The *incentive criterion* must be verified first, then only is the *security criterion* verified. Thus a car changes lanes only after having verified both criteria. Also a car (i.e. driver) wants to change of lane to obtain its maximum speed, or so that he or she doesn't have to slowdown. The forward visibility is once again important in order to obtain an optimal *incentive criterion.* This leads to compare the available space ahead on adjacent lanes.

To the best of our knowledge, none of these models attempt to replicate the overall behaviour of a multi-lane system using multi-abstraction levels: in the context of cellular automata approaches, space is represented as an uniform grid in which vehicles take decision. Instead we do believe that the behaviour of a multi-lane traffic system is based on human decisions which are taken at different levels of granularity depending on human driver profiles. Our proposed model will support such a principle using different levels of granularities in the cellular automata model and qualitative spatial reasoning, that is, different levels of spatial relationships between vehicles acting in a multi-lane environment. Moreover the precise modelling of such system must integrate variety and random in the type of individual behaviour, this is not currently the case in the above mentioned methods. In order to replicate this variety we propose a multi-agent modelling approach which is relatively efficient to simulate different knowledge at the microscopic level. Our work can be related to the one of Fernyhough et al. (1997). This research recognises and categorises traffic events from the analysis of video inputs. However the role of the prototype developed so far by these authors is to recognise and classify traffic events although our model proposes a simulation of a multi-lane traffic system from a micro-modelling point of view, individual behaviours being modelled at different levels of abstraction and using different types of knowledge and actions.

3. A multi-level traffic modelling approach

3.1 Spatial reasoning background

Artificial Intelligence reasoning has been widely discussed in terms of context dependent versus generic oriented model approaches that can be used in order to represent physical systems (Freksa and Röhrig, 1993; Burrough and Frank 1995, Mark and Frank 1996, Mujerkee 1998). Most approaches proposed so far have been generic; they identify spatial relationships based on either high-level cognitive concepts or elementary geometric primitives depending on the modelling viewpoint adopted. These models provide important theoretical backgrounds for the spatial analysis of physical systems. However, there is still scope for the development of context dependent relationships that satisfy the constraints of the represented domain in order to achieve a more efficient and realistic application. For example, many applications involve solid bodies, which then restrict the possible topological relationships to non-intersecting relationships. The spatial frame of reference, implicitly defined as an infinite one in most reasoning approaches, can also be constrained to a bounded plane or volume that further limits the set of plausible topological relationships. Representing spatial relationships is the first step towards analysis of the dynamics of physical systems. The second step involves the integration of time and the evolution of the represented system.

Spatial reasoning models use different assumptions and levels of abstraction. They are based on fundamental geometric properties of space or high-level cognitive concepts. On the one hand, geometric, often topological, models are based on possible and quantifiable relationships between basic spatial primitives (e.g., point, line, polygon, region) (Pullar and Egenhofer 1988, Egenhofer 1991, Randell *et al.* 1992, Clementini *et al.* 1993, Cui *et al.* 1993). They are formally defined but often limited to a countable number of spatial primitives (i.e., simple regions, regions with holes, unions of regions with a limited number of regions).On the other hand, cognitive models use and produce non-measurable qualitative concepts (Montello and Golledge 1999), e.g., the perception of the relative position/orientation of a body with respect to the position of the observer (cf. Freundschuh and Egenhofer 1997). Resulting relationships are often difficult to formally define and bound. Cognitive models are often applied to the description of common-sense spatial knowledge. For example, in (Egenhofer and Rodriguez, 1997), a relational algebra is used to model the relative spatial configurations of a mobile object with respect to a container and a surface in a room space, which act as the local frame of reference. The algebra identifies a set of minimal spatial relations and composition relations. Although the time dimension is not considered, this approach can be considered as context dependent because the table and the container constitute a constrained space in which the object is manipulated. Overall, cognitive models provide an alternative to quantitative models for the understanding of physical systems whose behaviour and dynamism are relatively complex and hence difficult to measure and evaluate with precision. They tend quite naturally towards application within cognitive systems such as robot motion planning (Latombe 1991), and human navigation in open-spaces or built-up environments to mention a few examples (Kettani and Moulin 1999).

The integration of geometric and cognitive properties of space is an avenue of research to explore. For example Edwards (1997) proposed a model which considers both geometric and cognitive properties of space. This model describes space-time events into two basic representational structures: views (the cognitive point of view) and trajectories represented as geometric references.

3.2 Multi-level spatial modelling

The modelling of our fictive system requires some form of spatial reasoning model, and the inference of rules and actions that simulate the behaviour of several concurrent vehicles. These imply the collaboration between different levels of abstraction and decision. In a landmark paper, Kuipers identified several distinct and complementary levels of description, that together form a hierarchical reference to develop inference and action rules (Kuipers, 1996). According to Kuipers, an agent acting in a local frame of reference is monitored through a first sensorimotor level that tracks the agent location. A second level, the control level, abstracts distinctive states and the evolution of such a system in a continuous mode. Both the first and second levels generate local knowledge of space. Then a third causal level models actions on those states. Finally a topological level represents the topological and metric properties of the represented system, providing then a global knowledge of the system.

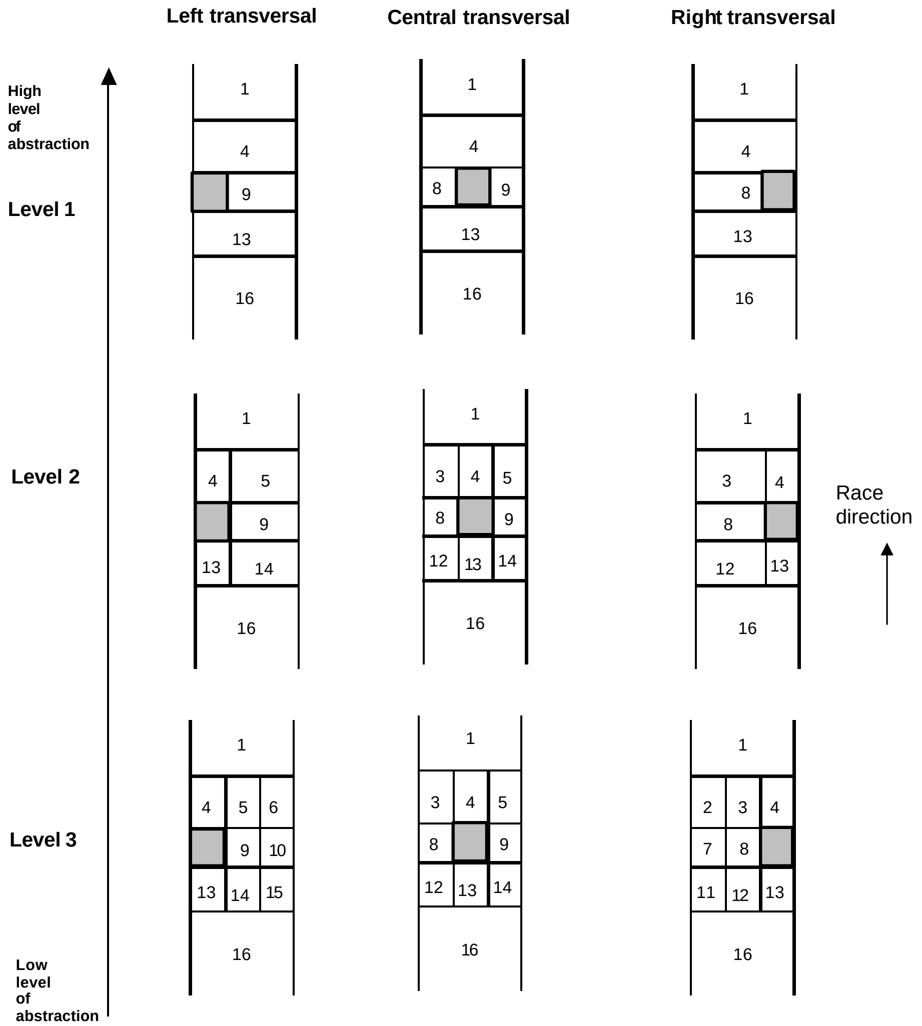
We propose a context dependent modelling approach in which the properties of the represented system are defined from the perception of the environment by some fictive agents within a local frame of reference. In such a local frame of reference, an agent produces a mental and visual representation of the appearance, behaviour and relative positions of the external objects (Jackendoff 1996, Frank 1998). External objects within this environment are perceived depending on influential factors such as proximity, salience and permanence (Tversky *et al.* 1998). An agent models a vehicle acting in a circuit of reference (i.e., a spatially bounded frame of reference). It perceives the environment through cardinal relationships that characterise its relative position with respect to external cars, and within the circuit of reference. Such cardinal relationships further support the modelling of inference rules that trigger a simulated system. This reproduces the evolution of several vehicles within a circuit, based on some basic hypotheses and parameters (e.g., initial speed, maximum speed per car). Cardinal relationships are modelled at different levels of abstraction. Each level supports different decision mechanisms for the simulation of the actions and behaviour of the represented cars.

In the context of our model, the inference system starts from a definition of cardinal relationships between the represented vehicles. Distinctive states and the continuous behaviour of these vehicles are then triggered from a set of initial parameters and their evolution within the local frame of reference (i.e., the circuit). Let us remark that our prototype system is a closed experimental system, the sensorimotor level is therefore not relevant here. Individual actions (i.e., displacement within the circuit of reference) are then derived according to some typical vehicle behaviours. An action is an egocentric decision taken at an individual vehicle level, and this action depends on an analysis of relationships with other cars within the circuit.

In order to identify reference relationships, let us introduce the basic principles of our system. A car's relationship to the reference circuit is modelled in terms of the linear location of the car within the circuit (a function of time and speed), and its relative transversal position within the same circuit according to three reference locations: at the left, in the centre, and at the right. A car's cardinal relationship to an external car is modelled in terms of its relative distance and orientation according to its transversal position. This can be considered as an application of Freksa's cardinal relationships (Freksa, 1992) to solid bodies constrained by a frame of reference. Figure 2 illustrates these concepts. The position of the reference car is approximated by a bounding rectangle (the polygon shaded in Figure 2), this bounding rectangle represents the immediate spatial environment that surrounds the car of reference. Relative positions to external cars are then derived from the analysis of the neighbourhood bounding rectangles, using different levels of abstraction as illustrated in Figure 2. Overall, 16 cardinal relationships are identified, in fact these form 8 pairs of converse relationships [(1,16), (2,15), (3, 14), (4,13), (5,12), (6,11), (7,10), (8,9)], according to the labels and identifiers given in Figure 2. The different levels identified in the figure represent the levels of abstraction used by our model (the lower the level of abstraction, the more precise the cardinal relationships and the inference rules are). These different levels of abstraction support different forms of inference rules and simulations. Some of these relationships can be generalised from higher to lower or from lower to higher levels of abstraction. For instance the cardinal relationships 3, 4 and 5 identified at the lower levels of abstraction are all generalised to a cardinal relationship 4 at the coarser level of abstraction. Similar generalisations apply throughout the cardinal relationships identified in Figure 2.

These cardinal relationships give a snapshot of a car of reference's relationships to an external car within the circuit of reference. These relationships are a function of time, that is, they are valid for a period of time (that can be an instant). The relationships identified in Figure 2 give sixteen mutually exclusive and complete cardinal relationships whose validity depends of the level of abstraction. The levels of abstraction used in the spatial and temporal dimensions are important parameters of the model; they are application dependent. The respective relationships of the car of reference to the circuit and external cars relative motion are functions of a temporal granularity, let us say for example, in the range of 0.1 second in a simulated circuit condition.

The evolution of a car's cardinal relationships can be modelled using an immediate sequence of events (if the events are continuously monitored) or by a relaxed sequence of events (if the events are monitored on a discrete mode). A given orientation between a car of reference and an external car is associated to a specific level of abstraction, and a particular transversal location of the car of reference within the circuit. These properties are denoted as follows:



1	Forward	2	Exterior left in front
3	Left in front	4	In front
5	Right in front	6	Exterior right in front
7	Exterior left	8	Left
9	Right	10	Exterior right
11	Exterior left behind	12	Left behind
13	Behind	14	Right behind
15	Exterior right behind	16	Backward

Figure 2: car's cardinal relationships at different levels of abstraction

Let Car_{ref} be a car of reference, Let Car_{ext} be an external car;

Let *tr* be the transversal position of a car of reference within the circuit, the domain of transversal positions is (*left*, *central*, *right*)

Let *level* be the level of abstraction used for the definition of the cardinal relationship between a car of reference Car_{ref} and an external car Car_{ext}. The domain of levels of abstraction is (*level1*, *level2*, *level3*).

Let *f* be a function that gives the set of cardinal relationships defined for a given level of abstraction and a transversal position. Then the range of *f* is defined as follows

f (*level1*, *left*) = {*forward, in front, right, behind, backward*}

f (*level1*, *central*) = {*forward, in front, left, right, behind, backward*} *f* (*level1*, *right*) = {*forward, in front, left, behind, backward*}

f (*level2*, *left*) = {*forward, in front, right in front, right, behind, right behind, backward*}

f (*level2*, *central*) = {*forward, left in front, in front, right in front, left, right, left behind, behind, right behind, backward*}

f (*level2*, *right*) = {*forward, left in front, in front, left, left behind, behind, left behind, backward*}

f (*level3*, *left*) = {*forward, in front, right in front, exterior right in front, right, exterior right, behind, right behind, exterior right behind, backward*}

f (*level3*, *central*) = {*forward, left in front, in front, right in front, left, right, left behind, behind, right behind, backward*}

f (*level3*, *right*) = {*forward, exterior left in front, left in front, in front, exterior left, left, exterior left behind, left behind, behind, backward*}

Let *s* be a cardinal relationship, defined on the range of cardinal relationships given at a specific level of abstraction, according to the above function *f*. A cardinal relationship between a car of reference, denoted Car_{ref}, with an external car, denoted Car_{ext}, at a given level of abstraction denoted *level*, is given by the function

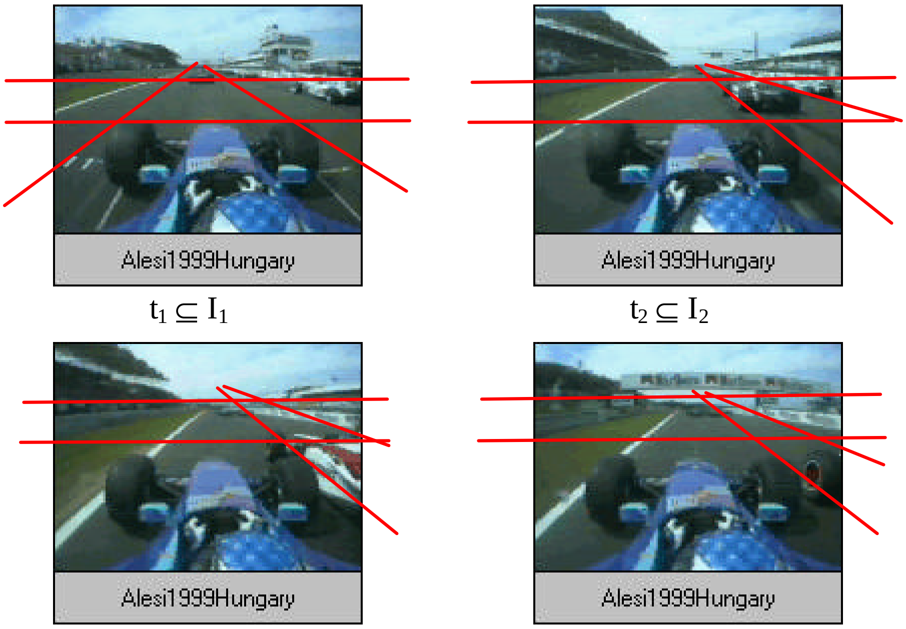
$$SR(Car_{ref}, Car_{ext}, level) = (tr, s)$$

With the constraint that for a given *SR*, $s \in f\,(level, tr)$

Then a sequence of cardinal relationships between a car of reference, denoted Car_{ref}, with an external car, denoted Car_{ext}, at a given level of abstraction denoted *level*, and over a period of time *I* is given by the function

$$Seq(Car_{ref}, Car_{ext}, level, I) = [\ (tr_1, s_1, I_1),\ \ldots, (tr_n, s_n, I_n)\ ]$$

With the constraint that $I_1, \ldots, I_n \subseteq I$ and $I_1, \ldots, I_n$ successive and non intersecting temporal intervals



$t_1 \subseteq I_1$ $t_2 \subseteq I_2$

$t_3 \subseteq I_3$ $t_4 \subseteq I_3$

Figure 3: Modelling example

Let us take the example presented in Figure 3. The front car, denoted *FrontCar*, is the modelling subject of interest. The cardinal relationships to model are the ones with the white car (the one that appears right in front in the first snapshot), denoted *WhiteCar*, using the four snapshots presented in Figure 2, with time intervals I_1, I_2 and I_3, for which these snapshots are respectively valid (with $I = I_1 \cup I_2 \cup I_3$). The sequence of cardinal relationships presented by Figure 2 is given as follows, first modelled at the level of abstraction *level3*:

Seq(*FrontCar, WhiteCar , level3, I*) =[(*centre, right in front,* I_1),(*left, right in front,* I_2),(*left, right,I*)]
At a higher level of abstraction, for example *level1*, the same sequence is defined as follows:*Seq*(*FrontCar, WhiteCar , level1, I*) = [(*centre, in front,* $I_1 \cup I_2$), (*left, right,* I_3)]

The above sequences denote some immediate sequences as the union of their periods (i.e., $I_1 \cup I_2 \cup I_3$) gives a convex period of time.

4. Modelling traffic behaviours: states and displacement rules

So far this model gives a static view of the evolution of the represented system: a snapshot of cardinal relationships between several cars in a circuit. The simulation of vehicle displacements within the circuit requires the definition of explicit rules. Different levels of inferences can be modelled: displacement rules defined for an independent car within the circuit, and relative displacement rules that consider the interaction and constraints between several vehicles navigating in the circuit. The former represents the less constraining level, while in the latter the complexity increases according to a function of the number of vehicles. We adopt the following two-step approach: relative constraints are first applied, then independent displacement rules are triggered under the constraints defined by relative displacement conditions.

The state of a car, denoted *car*, in the circuit at a time *t*, denoted *state*(*t*), is given by the location *loc*(*car*, *t*), transversal position *tr*(*car*, t), and speed *spd*(*car*, *t*) of that car, as follows.

state(*car*, *t*) = (*loc*(*car*, *t*), *tr*(*car*, *t*), *spd*(*car*, *t*))

car identifies a car; *loc*(*car*, *t*) gives the location, denoted *loc*, of a *car* at an instant *t*; where *loc* is given in grid units; *tr*(*car*, t) gives the transversal position *tr* of a *car* at an instant *t*; where *tr* is given according to the domain previously defined, that is (*left*, *central*, *right*); *spd*(*car*, *t*) gives the speed, denoted *spd*, of a *car* at an instant *t*; where *spd* is given in grid units per unit of time.

Without loss of generality, the circuit is modelled as a grid of n x m grid units where for demonstration purposes the following inferences are applied to the cardinal relationships identified at the level 2 of abstraction: in the remainder of this paper, we use a n x 4 grid in which the width of the circuit is compliant with the level 2 used for defining cardinal relationships, that is, 3 transversal grid units; where n represents the length of the circuit. In order to preserve generality, we choose a part of circuit schematised as a perpetual bi-directional route. We then model the relative displacement constraints of the system, based on Resnick's traffic example (cf. Resnick 1997, pp. 68). This example analyses the impact of local interactions on traffic congestion. A simplified rule to model car interactions can be described as follows: "***If*** a car in front ***Then*** overtake Or slowdown; ***Otherwise*** speedup". We take this simplified rule as a starting inference. Let us initialise a circuit in which several cars of interest are considered. Each car can be considered as an autonomous and intelligent agent with a form of local knowledge of space. A car's behaviour is based on a set of parameters defined for illustration purposes: a speed limit and an initial speed both defined randomly. During the simulation a car experiences several actions such as displacements along the circuit, speed increases and decreases, transversal positions *tr* change, and overtaking events. The identification of the next transversal position of a car is specified thanks to an algorithmic approach (formulated in textual form for presentation purpose):

> *The possible transversal positions given by state(car, t+1) with respect to a state(car, t) are given by the permissible ones amongst the neighbourhood relationships "in front" 3, 4, 5 and 6. This gives two alternatives for tr values left and right, three for a tr value centre). Amongst the possible transversal positions, first the algorithm identifies which ones are unoccupied*

(i.e., the permissible ones), keeping the current one whenever possible or taking a neighbourhood tr on a random basis, that is, an overtaking decision.

In order to calculate the next displacement of a car within the circuit, different cardinal relationship configurations are analysed according to the car's transversal position and external relationships. Let us for instance introduce a skeleton algorithm applied to the transversal position *left* at the second level, according to Figure 2. This case corresponds to the subset of cardinal relationships given by f (*level2, left*), and by analysing cardinal relationships in front or at the same linear location assuming that cars' behaviours are driven by such conditions in first approximation (cardinal relationships "behind" are then excluded). The algorithm defined for this case is as follows (given in pseudo-code):

Algorithm

```
  tr(car, t)= left    /Case left
  If (a car front and no car right in front and a car in right) Or
  If (a car front and a car right in front and a car in right) Or
  If (a car front and a car right in front and no car in right) Then
      decrease speed in the range of the speed of the car in front,
      calculate the next location
      keep the current transversal position
check that the grid unit given by the next location and transversal position is unoccupied, if not
calculate another transversal location for this next location, if there is no other transversal
position free, then come back to the current location, modify the speed accordingly and find a
suitable transversal position
  If (no car front and a car right in front and a car in right) Or
  If (no car front and no car right in front and a car in right) Or
  If (a car front and no car right in front and no car in right) Or
  If (no car front and a car right in front and no car in right) Or
  If (no car front and no car right in front and no car in right) Then
      increase speed accordingly
      calculate the next location
      calculate the next transversal location according to algorithm (1)
check that the grid unit given by the next location and transversal position is unoccupied, if not
calculate another transversal location for this next location, if there is no other transversal
position free, then come back to the current location, modify the speed accordingly and find a
suitable transversal position
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The above rules are generalised under the same principles for the different cardinal relationship configurations identified. The next state of the system is identified when all next car's states are identified. These algorithms are processed in cycle until the end of the simulation.

5. Simulation experiment

5.1 Prototyping environment

One of our objectives is to analyse the impact and value of a qualitative spatial model on the behaviour of a constrained frame of reference in which several agents act independently. The implementation of such a qualitative reasoning model, based on individual agents, requires an adapted software environment. The simulation and modelling of agent behaviours have received much attention over the past years. Many software programs have been produced for the exploration of complex behaviours of autonomous adaptive agents in reality. Among others, *StarLogo*, developed by MIT media Laboratory, allows thousands of agents to interact and provides a variety of functions for the purpose of simulating complex adaptive systems (Resnick, 1997, cf. http://www.media.mit.edu/starlogo/). *StarLogo* provides three main modelling concepts, so-called agents, patches and the observer. Agents act in a regular two-dimensional cellular space, while the observer initialises and monitors the activities of agents and patches that give the physical constraints of the environment. Among others, *StarLogo* has been used to model complex systems in a variety of disciplines such as biology, chemistry, physics, urban and earth sciences (Jiang 1999; Batty and Jiang 2000). *StarLogo* offers a rapid prototyping and open software environment that supports the integration of spatial properties, the definition of explicit inference rules, and generation of a simulated system that replicates several agents (i.e., the vehicles) acting in a constrained frame of reference (i.e., the circuit).

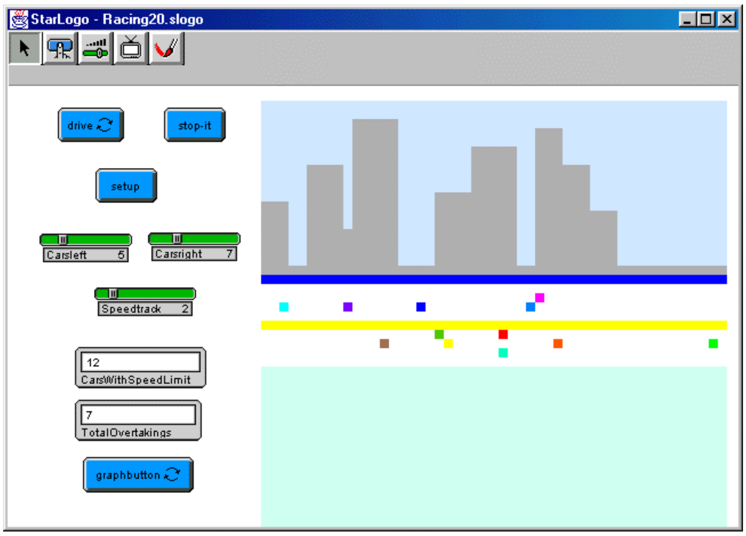

Figure 4 Simulation experiment - interface

In the context of our prototype, agents model vehicles, and the constrained space is the circuit that regulates the displacement of those agents. Let us introduce the principles of the prototype we have developed so far. This simulation prototype models the behaviour of several cars acting in a circuit of reference. The simulation is interactive as the user can define several initial parameters such as the number of cars per lane, i.e., left and right, and the global speed of the circuit that gives an overall speed to the simulation (Figure 4). The latter parameter allows us in fact to interactively change the speed of the simulation. The simulation interface is divided into a control window and a graphic window. The control window supports the initialisation of the simulation while the graphic window provides the continuous visualisation of the progression of the simulation and the cars' behaviour within the circuit. The following figure presents the layout of the circuit used for prototyping purposes. This circuit is represented as a perpetual bi-directional road, that is, a cycle: cars that disappear at the left (res. right) reappear at the right (res. left). The small square patches denote vehicles in the circuit. The figure below presents a typical simulation with 5 cars left, 7 cars right and a circuit that supports "high speeds" (e.g., speed track value of 10). Each car is initialised with a random speed limit giving then different individual speed behaviours within the circuit.

The overall behaviour of the environment is controlled by several monitors that indicate the number of vehicles that have reached their speed limit, and the total number of overtaking events over time. The controls give an assessment of the circuit behaviour over time. We can remark that the lower the number of vehicles, the more likely the circuit will reach an equilibrium state over a short period of time. The circuit presented on Figure 4 is snapshot of the initial circuit state after several overtaking decisions.

Inference rules, based on cardinal relationships, have been implemented. A typical overtaking example is illustrated by the following two simulation sequences. Figure 5a illustrates a single overtaking event that involves two cars involved (open overtaking choice), Figure 5b, an overtaking event with three cars involved (constrained overtaking choice).

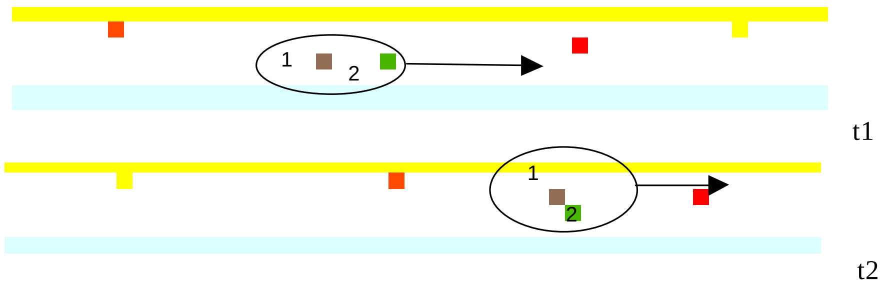

Figure 5a: single overtaking event

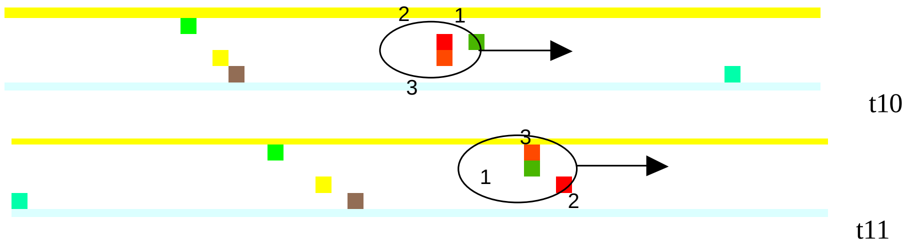

Figure 5b: Several overtaking events with multiple choices

5.2 Calibration

The previous section shows a first form of validation, that is, the way overtaking events occur during the simulation. A second important validation concerns the flow/density function and the overall pattern that needs to be observed: the traffic flow breakdown. Such a calibration requires an experimental validation on several computed simulation, and some initial decision on the simulation parameters (levels of abstraction, acceleration vs. deceleration). The observed result is that the introduction of different levels of abstraction still complies with the density versus flow graph. Modifying the acceleration/deceleration parameters in function of the density provides a valid way of approximating the flow/density relationship (using different values of acceleration/deceleration in algorithm 2). This confirm the observed fact that the logical structure of traffic micro-simulation determines the emergent behavior, not the details of the driving rules. In fact in decentralized simulations, microscopic differences can often be leveled by a macroscopic view of things. Nagel and his colleagues have also put forward the fact that driver behavior is a very subjective notion (Nagel *et al.* 1997). Figure 6 illustrates our findings with simulation results compared to the flow/density relationship. Additional snapshots on that figure shows some typical circuit patterns.

General occurrences of traffic dynamics can be observed. At low densities the simulation produces a laminar flow and jams seldom happen, and when they do, they usually clear up fast. Likewise, at higher densities, after the *point of traffic flow breakdown*, traffic is a composition of jams and “free flow regions”, as is observed in reality. The traffic jam regions become more and more extensive with increasing density, as is observed in traffic dynamics on real freeways. Asymmetric lane changing rules there is a phenomenon called *density inversion*. This terminology is used in two-lane traffic (Kraub *et al.* 1999) when the usage of the right-lane becomes superior to that of the left. On a three-lane freeway *density inversion* is when the two left-most lanes’ usage is superior to that of the right. This occurs in our simulation at densities around the *point of traffic flow breakdown*. Likewise, above a certain density the lane-usage becomes equal on every lane which is due to a generalised traffic jam.

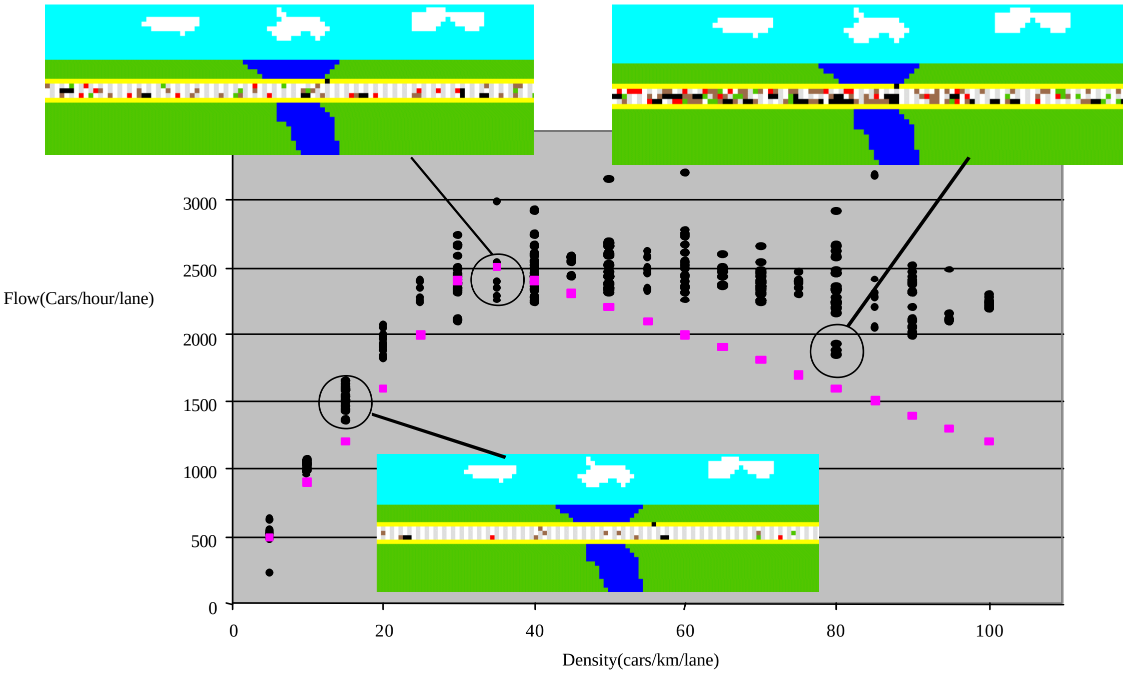

Figure 6: Flow/density calibration

6. Conclusion

Spatial reasoning provides several avenues to explore for the simulation of complex physical systems. However there is still a need to adapt theoretical spatial reasoning models to the particular constraints of the domain of study. This paper illustrates a context-dependent spatial reasoning approach, based on cardinal relationships. We model relationships between several cars acting in a multi-lane circuit at different levels of abstraction, and by considering the spatial constraints of the circuit of reference. Context-dependent cardinal relationships support the inference of displacement rules within the circuit. The potential of the model is demonstrated by an agent-based prototype that integrates these spatial reasoning principles and model displacement rules.

Overall the prototype provides an illustration of the benefits of spatial reasoning and an interactive interface to interactively simulate the behaviour of the represented system, using several initial conditions and different levels of abstraction. Under the conditions of our simulated system, the prototype demonstrates that these cardinal relationships support the simulation in an effective way, the simulation prototype has been calibrated using the flow/density law. A simplified animated movie of the prototype is available at (http://www.hig.se/~bjg/RACING-MOVIE.mov), the full version of our prototype with source code at (http://www.hig.se/~bjg/source-code.html), and the StarLogo program at (http://www.media.mit.edu/starlogo/). We plan to extend the prototype to contexts that replicate complex urban traffic conditions.

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