A realistic cellular automata model for multi-lane traffic considering drivers' profiles effects

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Abstract

The increase of vehicles traffic flow adversely affects people's lives in modern societies, and their physical distribution in an urban environment. Traffic jams and their associated generation of pollution, are some of the reasons why a better understanding of traffic flow has received so much attention. Many mathematical models have been employed in the last decades in order to study and understand traffic flows characteristics. In this work we present a multi-lane extension of a recently proposed cellular automata (CA) model for traffic flow that makes possible the consideration of different profiles of drivers' behaviors with a realistic approach. In this model two uncoupling steps allows us to consider the influence of different drivers' behaviors in traffic: we first infer the motion expectation in front of each car and, after this, define how this car decides to get around, considering traffic configuration ahead of it. To do this one uses the Beta Distribution Probability Density Function (PDF), with accept-rejection technique of Monte Carlo method to define these behaviors. The same approach is used to define lane changes and overtaking rules to represent different drivers profiles. This approach allows us to present a robust and realistic computational model for traffic on roads with two or more lanes able to represent traffic physical collapse, allowing the assessment of highway capacity and of their synchronized flow, among others traffic flow characteristics.

Keywords: traffic flow model, multi-lane model, cellular automata, driver's behavior

1. Introduction

The understanding of the dynamic of traffic, with causes of congestion occurring on non signalized multilane highways and freeways is very important for effective traffic management, control, organization, and other engineering transportation applications. Numerous models, macroscopic and

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microscopic, have been proposed in recent years to describe vehicular traffic. While macroscopic models view traffic as a one dimensional compressible fluid, microscopic models, as those based on Cellular Automata (CA), focus their attention on the behavior of individual vehicles and on the influence of neighborhood vehicles [1, 2, 3].

Microscopic models, based on Cellular Automata, have been widely used, existing today an extensive amount of research addressing various numerical techniques for models of this type. These CA models for traffic flow (TCA) are discrete, in time and space, and properties of the CA must have only a few number of states. Despite its simplicity, CA is able to represent the different stages of traffic flow, including the metastability region, being also able to capture some essential features observed in realistic traffic.

In recent years there has been a great effort to model human behavior in traffic [4, 5, 6, 7]. Recently Saifuzzaman [8] presented a literature review with specific focus on the latest advances in car-following models to include human behavior. In [7, 9] we presented a stochastic cellular automata model, in order to simulate traffic, which is an anticipation model, where we described, in organic way, the effect of the different drivers's profiles. To do this, it used a Probability Density Function (PDF) of the Beta Distribution in such way that three different drivers behavior were obtained only by changing its parameters. However, a realistic description of the traffic dynamics requires to take into account complex road structures peculiarities, such as multi-lane roads. Several multi-lane model [6, 10, 11, 12] were proposed for highway traffic as well for urban traffic networks in order to reproduce the empirically observed lane usage inversion.

In this work we present an extension of the model presented in Zamith et al [9] for multi-lane roads where drivers profiles are considered in the rules. For this, in Section 2 we first present the single-lane model for CA with different drivers profiles. Section 3 presents the multi-lane model with lane change rules, followed by some conclusions on the last Section.

2. One-lane model with drivers behavior definition

Before we present the lane changing rules, let us briefly define the single-lane model of cellular automata used in this work [9]. It is an anticipation model that enables the consideration, in a efficient way, of different drivers' behaviors profiles. To represent multiple vehicle types, defined by the number of occupied cells (li), and different acceleration policies, a multicell representation was adopted. In our metric, a standard vehicle occupies 5 cells of a regular discretized road where each individual cell size corresponds to

1.5 meters. This discretization allows the model to represent a comfortable steering style, compatible with drivers profiles.

2.1- The model

The driving strategy is defined by two stages: one related to the prediction of the effective distance that each vehicle can move at each time step (d_{is}), and another related to the definition of its desired velocity and of the effective movement of each vehicle having in mind those distances. Uncoupling these two steps allows us to consider the influence of different drivers behaviors in traffic. The model implements stochastic rules for defining cars movement expectation ahead of each concerned vehicle and for the adjustment of their velocities.

At the first stage we consider the effective distance (d_{is}) between vehicles i and $i+1$. It is considered that the last one keeps unaltered its motion, and it may accelerate if possible. The definition of this acceleration depends on the random variable α, as stated in Eq. 1, where $\mathrm{int}(x)$ defines the integer value closer to x.

$$d_{is}^{t+1} = max\{d_i^t + min[v_i^{t+1} + int(\delta v(1-\alpha)), d_{i+1}^t] - ds, 0\} \tag{1}$$

With this definition, the vehicle $i+1$ can maintain its velocity, if $\alpha = 1$ and can accelerate up to a maximum value δv if $0 \leq \alpha < 1$. It can also decrease its velocity in case there is some vehicle, immediately in front of it, restricting its movement (d_{i+1}^t). Besides that, the value of safety distance, d_s, is also considered for obtaining the effective distance, which can reduce the value of d_{is} when necessary. Safety distance is necessary to avoid collisions. In the second stage, the desired velocity, the model allows the usage of several acceleration policies depending on the random variable α, defined by drivers' profiles, and on the defined maximum acceleration (δv) as shown in Eq. 2

$$v_i^{t+1} = min[v_i^t + int(\delta v(1-\alpha)), v_{max}] \tag{2}$$

If $\alpha = 1$, the vehicle will keep its velocity and if $0 < \alpha \leq 1$ the vehicle will accelerate up to its maximum allowed velocity. If the distance between vehicles permits, the vehicle will move following the desired velocity. Otherwise it will reset its velocity to adapt it to the available space for its movement. To allow a more comfortable driving adapted to the driver's profile, the model must use a more refined discretization than usual for the route. This makes possible to define different accelerations, and distances, in each time step. When $\delta v = 5$, for instance, we can increase the velocity by one cell per second until 5 cells per second (equivalent to 1 cell of $7.5m$ per second, as in conventional CA). The update rules included on this two stages algorithm are detailed on [9].

To model different drivers' profiles, the random variable α is modeled by a continuous Probability Density Function (PDF). Values of α_i close to 1 define more conservative behaviors both for the calculation of the effective distance and of the desired speed. On the other hand α values next to zero identify more aggressive behaviors.

2.2 Drivers profiles

In this model, drivers' profiles are given in an organic way, using a Probability Density Function (PDF) that can represent the behavior trends of these different profiles. To define values of α we use Beta function, with different parameters, with a Monte Carlo rejection process [7].

The Beta function ($f(x)$) is defined as:

$$f(x) = \frac{\Gamma(a+b)}{\Gamma(a)\Gamma(b)} x^{a-1}(1-x)^{b-1} \tag{3}$$

with $0 \leq x \leq 1$ and $\Gamma(n{+}1)$ function depicts a factorial of number $\Gamma(n{+}1) = n!$, $n > 0$ is a positive integer. Fancher et al. [14] identified classes of behaviors, taking into consideration a person tendency to drive faster or slower and to stay closer or farther from the upfront vehicle. Based on this reference, in this work we assume the following behaviors:

Daring: describes the behavior of a driver that intends to go fast and to stay close to the upfront vehicle. In this case we assume the same parameters for distance and velocity for the Beta function: $a = 1$ and $b = 4$.

Slow: describes the driver with the opposite profile of the daring. This driver prefers to maintain a great distance of the upfront vehicle and drives slower. We also call this driver ultraconservative. Beta function parameters: for distance, $a = 15$ and $b = 1$ and for velocity, $a = 6$ and $b = 6$.

Standard: describes a driver that is not characterized by none of the previous profiles and that intends to go according with the flow. In this case we use a symmetric functions with the following parameters: distance, $a = 9$ and $b = 5$ and for velocity, $a = 5$ and $b = 9$.

2.3 - Simulation results of the cellular automata model

To show some results of single-lane model with drivers' behaviors we adopt a circular highway, under periodic boundary condition, composed by $20,000$ cells of $1.5m$. The simulations were executed using highway densities ranging from 0.01 up to 0.99, with $20,000$ time units. The results for the first $2,500$ units were discarded, since we were not concerned with transient effects in this simulation. On these tests we used $v_{max} = 25$ cells/s for daring and standard behaviors and for slow driver we adopted $v_{max} = 22$ cells/s and $\delta_v = 5$. Figure 1 presents the fundamental diagrams for three drivers' profiles and in Figure 2 real data for flow-density diagram for Northbound lanes on Interstate 80 in Hayward, California [15]. For comparisons purposes in Figure 2 flow is measured in cells by seconds and density as the percentage of occupied cells in our lattice, which means that a flow of 0.4 corresponds to 1500 vehicles per hour while 0.77 corresponds to 2700 vehicles per hour and also means that a density of 0.84 corresponds to an occupation of 180 vehicles in each mile with cells of 7.5 m of length. We can observe by

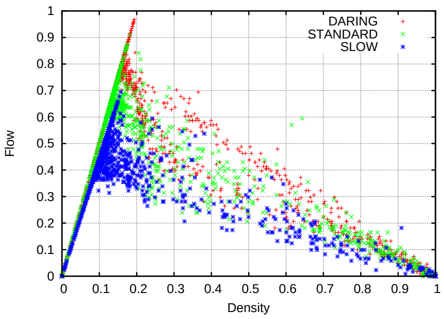

Figure 1: Fundamental diagram (Daring-standard-slow results)

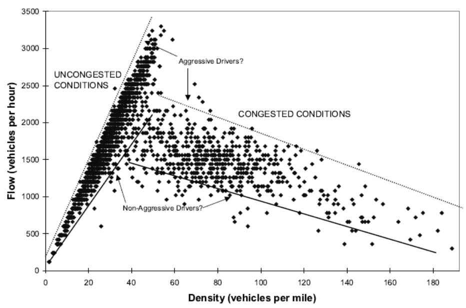

Figure 2: Real data fundamental diagram

these graphics that the model represents, with good quality, the three states observed in real traffic flow and different drivers' profiles.

3 Multilane model with drivers behavior

Lane changing rules can be symmetric or asymmetric. While symmetric rules treat both lanes equally, asymmetric lane changes rules are dominated by a preference lane, and right lane overtaking banned. Different criteria apply for the lane change from left to right and right to left. In this work we modify lane changes rules, proposed in [12] based on asymmetric traffic rules using effective distance concept. In these rules, first, a vehicle needs an incentive to change lane. These conditions are necessary for lane changing but not sufficient: a lane change is only possible when some safety constraints are fulfilled. The α parameter used in subsection 2.1 for defining drivers' behavior is also used to define a driver's motivation to overtake a vehicle. As usual, in case of overtaking, a time step of time is decomposed in two sub-steps: initially, cars only change lanes according to the lane changing rules and after this, cars move according to the CA model rules. Both sub-steps are performed in parallel for all vehicles.

3.1 - Changing lane rules

(i) Right to left:

Incentive criterions: The driver of each vehicle becomes motivated to a left lane change whenever it is at some pre-defined distance from the vehicle ahead of it, taking also into consideration its own velocity and if left lane shows a better flux condition, given by inequalities on Eq. 4.

$$h_i v_{i,j} > d_{is,j-1} \qquad \text{and} \qquad v_{i,j} < d_{is,j-1} \tag{4}$$

where $v_{i,j}$ is the velocity of i-th vehicle at j-th lane; $d_{is,j}$ is the effective distance of the i-th vehicle to that in front of it, $d_{is,j-1}$ is the effective distance of the ahead vehicle at left lane $(j-1)$ and $h_i > 1$ is a parameter that depends on the vehicle behaviour, given by $h_i = max[\alpha_i \times h, 1]$, which shows that a vehicle can be motivated to change lane even before it detects lacking space for its movement. In this way, with α values close to zero, the driver will be motivated to change lane when he is close to the ahead vehicle and if α values are close to one there will be an anticipation in this motivation.

Safety criteria: For safety reasons each driver, when changing lane, has to verify if there is enough space to accommodate its own vehicle in the new lane and to watch if it will not block some other vehicle at the target lane. To do this it must verify the position of behind and ahead vehicles at target lane, that is:

$$(d_{is-1,j-1} > v_{i,j}) \qquad \text{and} \qquad (v_{i,j} < d_{is,j-1}) \tag{5}$$

By the exposed criterion in Eq. 5 one verifies if the i-th vehicle will not block vehicle behind vehicle on the target lane when changing lane. To do this, one has to examine whether any vehicle on target lane can or not move with the required speed considering the anticipation strategy. Through the same equation/criteria one can verify if there is enough space at target lane by comparing vehicle velocity $v_{i,j}$ with the distance between it and vehicle $i+1$ taking into account that this last one are going to move on next time step.

(ii) Left to right

The rule for a left-right lane change considers whether analyzed vehicle moves more slowly than other vehicles on the same track and if it can return to the right lane.

Incentive criterions: The driver is encouraged to change lane when

$$d_{i,j} > h_a \times v_{i,j} \tag{6}$$

$$(v_{i,j} < v_{i-1,j}) \quad \text{and} \quad (d_{i-1,j} < h_b \times v_{i-1,j}) \tag{7}$$

By this criteria the vehicle is encouraged whenever a back vehicle $(i-1)$ is faster and near of i. In this case we use h_b parameter defined by drivers behavior, and evaluated by $h_b = max[2h\alpha, 1]$. The driver also feels motivated to return to right lane when he observes that vehicle $i+1$ moves away from him, as described by these inequalities. The h_a parameter, function of drivers behavior, is defined as $h_a = max[h\alpha, 1]$. We used here $h = 12$ as proposed by [7].

Safety criteria: The safety rules for changing lane from left to right are similar with those described on item i.

In order for the described model not become characterized by an excessive amount of lane changes, due to ping-pong effect, an analysis was provided to adjust the amount of lane changes. Results shown on Zamith [7] concluded that for the 50% probability for lane change model can be compared with those presented by [12, 11] for asymmetric lane change rules. This probability was used in this work.

3.3 - Simulations results

In this section we present results for two-lane model for homogeneous and non-homogeneous lanes, with different drivers and vehicles sizes. In Fig. 3 the fundamental diagrams of the two lanes are shown for a standard driver. We considered a composed two-lane road with $20,000$ cells with 1.5 m each. The simulations were executed for $20,000$ time units and results for the first $2,500$ units were discarded. We also consider $v_{max} = 25$ cells/s and $\delta v = 5$. These diagrams show, for the individual lanes, that the maximum flow on the left lane is greater than the maximum flow on the right lane, which agrees with real data. As in [12], the maximum flow is reached at a lower density on the right lane than on the left lane. It can be observed, in velocity distribution of two lanes shown in Figure 4, a clear distinction between the free flow and the congested state. At lower densities the average velocities remain constants at a high value (v_{max}). When the density increase, velocities drop occurs, remaining in constant declination with smallest velocity in the right lane, until higher densities, when average velocities are the same in both lanes. In this way the model represents the separation of the system in fast and slow lanes, indicating that the speed is always larger on the left than on the right lane.

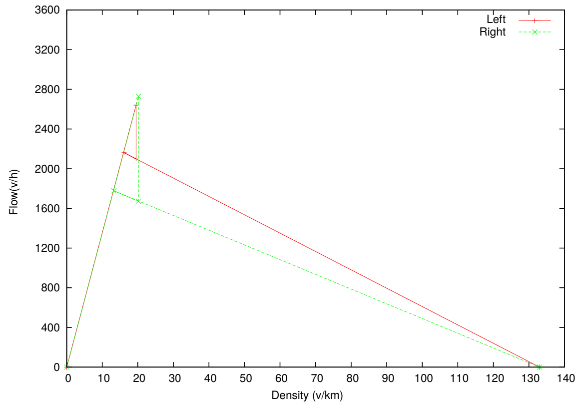

Figure 3: Fundamental diagram (beta function - a = 4, b = 8)

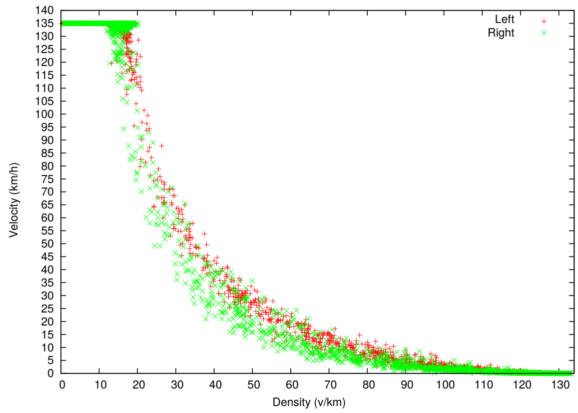

Figure 4: Velocity-flux Diagram

Next, we considered an inhomogeneous model with trucks and cars. Trucks are considered slow vehicles, with slow drivers, and each one occupies 10 cells and have a maximum speed of 15 cells per second as suggested by Knospe et al. [12]. In Figure 5 we present results for flow-density diagram when there are, on the road, 10% and 40% of trucks with v_{max}, in this case adopted as 18 cels/s and $\delta v = 4$. Although there is no requirement that trucks do not move through right lane, they for being slower vehicles, have the tendency to stay at the this lane. We can see that the model displays well this feature even on free flow region.

4. - Conclusions

In this paper we present an anticipation model for a multi-lane road

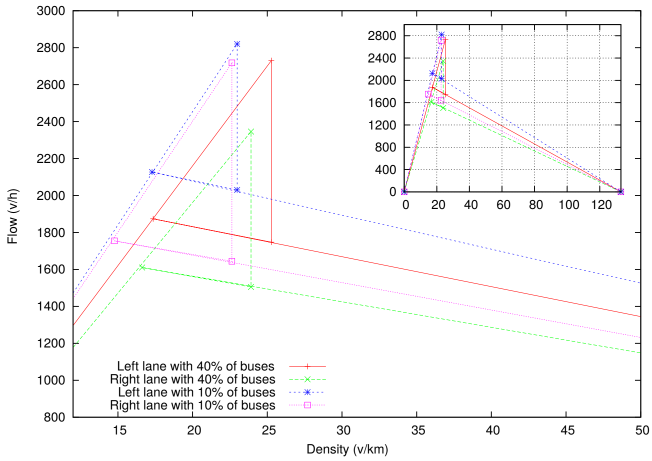

Figure 5: Flux-density Diagram - slow and standard drivers

and an asymmetric multi-lane model. We saw that a simple modification in the Probability Density Function can better capture driver reactions and describes the three states of flow: free, synchronized and traffic jam. Simulations results prove that this model can reproduce traffic flow phenomena, making the model closer to real highway behavior. Moreover, it preserves simplicity of CA model and at the same time with an intuitive explanation for all rules. Results obtained for one or more lanes, with homogeneous and inhomogeneous drivers, shown that the model reproduces phenomena observed in real traffic flow with quality and includes the density dependence of the number of lane changes or the lane usage even using different types of cars and drivers.

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