Modeling the conscious behavior of drivers for multi-lane highway driving

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ABSTRACT
The current state of the art in simulating highway driving extensively relies on models using formulas similar to those describing physical phenomena such as forces, viscosity or potential fields. While the parametrization of these formulas can account for the limitations of the driver (such as reaction delay), they are badly suited for modeling conscious behavior. In this paper we describe our simulation architecture which uses an agent-based model to represent the conscious tactical and strategic behavior of the agent. This model will act as a high level input to a state-of-the-art virtual physics model which models the physical vehicle and the subconscious aspects of the driver behavior.

The concrete aspects of driving modeled in this paper are the strategic lane preferences of the drivers, with a special attention to the optimal lane positioning for a safe exit. We have used the model to simulate the traffic on Orlando's Highway 408. The results match well with the real world traffic data. The increased simulation detail can be applied to crash prediction and the control of intelligent transportation system devices, such as variable speed limits.

1. INTRODUCTION
Existing microscopic traffic simulation models heavily rely on mathematical formulas similar to those describing various physical phenomena: forces, viscosity, potential fields and so on. We will call these *virtual physics* models. Over the course of the last fifty years there was a gradual shift from formulas relying on fluid dynamics towards the individual treatment of the vehicle as a particle subject to a collection of forces.

These models have been proved predict well the integrative, long term parameters of the traffic, such as throughput or average speed in congested traffic. These values are highly useful for making long-term decisions such as highway planning. Their level of detail, however, is insufficient to model events depending on specific driver decisions – such as the incidence of crashes. On the other end of the spectrum, we find purely agent based simulators such as the NetLogo [9] based `http://ccl.northwestern.edu/netlogo/models/Traffic2Lanes`. These efforts are successful as proofs of concepts, yet their realism and simulation accuracy is arguably lower than state of the art virtual physics models.

Our work is centered on improving the accuracy of microscopic highway simulation through agent based modeling of the *conscious* aspect of the driver behavior. These type of models are sometimes called "nanoscopic" traffic simulations [6, 3]. Lower level behavior, such as the vehicle physics, the driver's reflexive action, and those aspects of the driver's behavior which have been learned to the point of becoming automated will be handled by the virtual physics model augmented to allow for the integration of the agent based component. For the starting point of the contributions described in this paper see [5].

The conscious part of the driver's behavior can be classified into strategic and tactical behavior. Strategic behavior involves decisions which are planned for the overall success of the drive (safe and fast arrival to the destination). Examples involve route planning, joining or leaving convoys, and choosing the appropriate highway lanes. Tactical behavior includes actions taken to achieve short term advantages: overtaking a slow moving vehicle, escaping from a dangerous situation, increasing the distance from an erratically moving vehicle and so on. Our technical approach will be to separate the behavior of the driver into three simulation modules, as described in Figure 1.

The virtual physics model models the physics of the vehicle as well as those aspects of the driver which are either reflexive (such as emergency braking) or learned to the point of becoming sub-conscious (such as lane following and keeping a constant distance from the car in front). Our current model is based on [5], but we shall investigate other models as well.

The agent model models the conscious cognition of the human driver. This includes both strategic planning (which exit to take, which lane to prefer for long distance driving) and tactical (the decision to join a convoy or overtake a slow moving car). The agent model will receive input from the environment (including sensor data, signaling data, vehicle-to-vehicle and vehicle-to-infrastructure communication). The agent model acts *through* the virtual physics model, by tem-

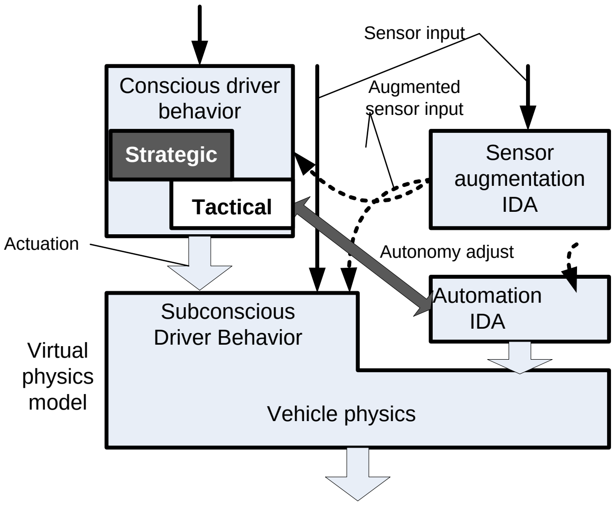


Figure 1: Overall architecture of the simulation model integrating the virtual physics model, the human agent and the automation model.

porarily changing its parameters, which, when the action is finished, will return to default values.

The automation model which models the action of the driver assist technologies, such as intelligent cruise control, emergency brakes, lane following and others. This component *replaces* the virtual physics model with a separate control system. The transitions between the virtual physics and the automation model need to model the real world transition of control between driver control and automation.

Due to space limitations, this paper will concentrate on a single, important aspect of strategic behavior, the planning, decision and execution of lane changes. For an even more concrete focus, we describe in detail the planning for a safe exit from a congested highway - which requires a number of lane changes ahead of the exit. It was found that about 10% of the crashes occurring on highways are *sideswipe crashes* while about 11% of them are *angle crashes* [7]. Both types are associated with lane changes (the reminder of the crashes are mostly rear-end crashes). Modeling the mechanics of this process is of a major importance as it can predict traffic simulations with high crash risk.

The reminder of this paper is organized as follows. Section 2 describes the virtual physics models which are the baseline of the contribution described in this paper. Section 3 describes the model through which the agent's preferences for specific lanes are enacted. Section 4 introduces a probabilistic model of success for lane changes. In Section 5 we apply the model to the problem of safe exit/merge from highways. We apply our work on the simulated traffic of Orlando's Highway 408 in the real world traffic data. We conclude in Section 6.

2. VIRTUAL PHYSICS-BASED MODELS

As shown in Figure 1, our agent-based driver model is closely integrated with and acts through the virtual physics model. To motivate this architecture, and to provide the foundation for the presentation of the agent model, we will briefly describe a collection of technologies which together are a good sample of the state of the art in virtual physics based models. These components will be used in our system to model vehicle physics and subconscious driver behavior. The virtual physics model has three main components: a time-continuous car following model, a lane change model and a human driver model.

2.1 Car following models

Car following models describe the behavior of a car on a single lane highway. Most such models calculate the acceleration or deceleration of the car though a formula of the following general pattern:

$$\frac{dv_i(t)}{dt} = f(\Delta x_i, v_i, \Delta v_i) \tag{1}$$

where $\Delta x_i = x_{i+1}(t) - x_i(t)$ is the distance between the vehicle and its immediate leader, and $\Delta v_i = v_i(t) - v_{i+1}(t)$ is the approaching speed. The specific formula we choose to use is the one introduced by Treiber et al. [10]:

$$\frac{dv_i(t)}{dt} = a\left[1 - \left(\frac{v_i}{v_0}\right)^4 - \left(\frac{\delta(v_i, \Delta v_i)}{\Delta x_i}\right)^2\right] \tag{2}$$

where a is the maximum acceleration of the vehicle, v_0 is the desired speed, and $\delta(.)$ is the desired distance from the leading vehicle. This distance depends on a number of parameters through the following formula:

$$\delta(v_i, \Delta v_i) = \Delta x_{min} + v_i T + \frac{v_i \Delta v_i}{2\sqrt{ab}} \tag{3}$$

where Δx_{min} is the minimum distance in case of congestion ($v_i = 0$), T is the safe time headway which models the buffering time of the driver, and b is the comfortable deceleration, which couldn't be less than -9 m/s^2 on a dry road.

Let us now discuss the intuitions behind this formula. On a free road, the instant acceleration changes from the maximum acceleration a (when the vehicle is still $v_i = 0$) to 0 (when the vehicle reaches its desired speed $v_i = v_0$). If a vehicle follows a leader with a negligible approaching speed ($\Delta v_i \approx 0$), the term $v_i T$ in Equation 3 dominates such that the vehicle maintains a distance $v_i T$ from the leader.

In the situation when the vehicle approaches the leader with a high speed, the last term $v_i \Delta v_i / 2\sqrt{ab}$ dominates and the formula dictates a deceleration. The most extreme case is when the vehicle moves with its desired speed v_0 and observes a still obstacle at the distance of x_i. To avoid a collision, the vehicle must brake with deceleration $-b$ when it reaches a distance of $\Delta x_i = v_i^2/2b$. Indeed, this is exactly what the model predicts:

$$\frac{dv_i(t)}{dt} = -a\left(\frac{\delta}{\Delta x_i}\right)^2 = -a\frac{\left(\frac{v_i \Delta v_i}{2\sqrt{ab}}\right)^2}{\Delta x_i^2} = -\frac{v_i^4}{4b\Delta x_i^2} = -b \tag{4}$$

The car following model, defined in this way is considered *collision free*.

2.2 Lane changing models

Our baseline model extends the car following model with the lane change model described by Kesting et al. [2]. This model assumes that lane changes happen instantaneously: for a shift to the left lane, a vehicle which has been previously in the middle lane, at time t disappears from the middle lane and appears in the left lane. This opens the possibility that a car, coming from behind in the new lane with a higher speed can not break sufficiently quickly and collides with the lane changing car. The model assumes that it is the responsibility of the lane changing car to ensure that the rear left vehicle $j-1$ has sufficient buffer distance such that it can decelerate before hitting the lane changing vehicle

$$\hat{a}_{j-1}(t) \geq -b_{max} \tag{5}$$

If this condition is not satisfied, the vehicle concludes that it is not safe to change lanes.

The second feature of the lane changing model is the analysis of the motivations to change lanes, and the "politeness of the drivers". We assume that the goal of the vehicles is to achieve their desired speed, which implies a certain desired acceleration $\hat{a}_i$. The motivation of the driver to change lanes is such that it can achieve this acceleration (which, we assume, is not achievable in the current lane). However, the changing of lanes might also trigger accelerations in the other vehicles: for instance, it allows the current follower to accelerate, and it might force the new follower to brake.

The notion of *politeness* models the fact that the driver might consider the accelerations of the other vehicles as well when taking a decision to change the lane. The politeness parameter p specifies how much does the vehicle discount the other vehicles' desired acceleration compared to its own. A value $p = 0$ indicates an impolite, fully selfish driver which does not care about other drivers (however, it still considers the safety criteria). The vehicle i will decide to change the lane if the following inequality is verified:

$$(\hat{a}_i + p \cdot (\hat{a}_{j-1} + \hat{a}_{i-1}) - (a_i + p \cdot (a_{i-1} + a_{j-1})) \geq \Delta p_{th} \tag{6}$$

where Δp_{th} is the politeness threshold. The left hand side is the difference between the new accelerations $\hat{a}_i$, $\hat{a}_{j-1}$ and $\hat{a}_{i-1}$ if the vehicle i successfully changes into the target lane and the old accelerations a_{i-1} and a_{j-1} if it doesn't change lane. The intuition is that the vehicle favors to change lane only when the advantage of the action is greater than the disadvantage it exerts to its neighboring vehicles. However, because the vehicle i can not obtain the parameters (T, v_0, a, b) for its successor $i-1$ and $j-1$, the utility of lane change can only be calculated by vehicle i's own parameters.

2.3 Human driver model in the virtual physics approach

A human driver is in some aspects "less capable", but in other aspects "more capable" than the abstract driver envisioned in the models considered up to this point. State of the art microscopic traffic models consider some aspects of the human driver such as reaction time, fatigue and cognitive limitations and integrate them in the equations of the virtual physics model.

For instance, our baseline model inspired from Treiber et al. [11] implements the following aspects. First, we consider the fact that humans can not perform an indefinite number of decisions per unit of time. This is modeled by considering a time step Δt. At every time step Δt the drivers observe the traffic and make a decision about acceleration. This acceleration value will remain constant for the next interval Δt:

$$\begin{aligned} v_i(t + \triangle t) &= v_i(t) + \dot{v}_i(t)\triangle t \\ x_i(t + \triangle t) &= x_i(t) + v_i(t)\triangle t + \frac{1}{2}\dot{v}_i(t)\triangle t^2 \end{aligned} \tag{7}$$

Another aspect of the human behavior modeled is the reaction time T' necessary to reason about the traffic situation and make decisions accordingly. This can be achieved by substituting in Equation 1 the current state (Δx_i, v_i, Δv_i) at time $t - T'$. If $t - T'$ falls between two simulation steps, then it will be adjusted as:

$$x(t - T') = \beta x_{t-n-1} + (1 - \beta)x_{t-n} \tag{8}$$

2.4 A critique of virtual physics models

Virtual physics integrate physical aspects (such as maximum acceleration a and maximum breaking b) with psychological aspects such as desired speed v_0, and even cognitive limitations such as the reaction time t_r. A well tuned virtual physics model can provide a good simulation of the overall flow of the traffic. It can not, however, model well the details of specific situations.

For instance, the model presented above assumes that the only justification for a lane change is to achieve a more favorable acceleration. This obviously covers only short term behavior, but even then, it fails to account for some important aspects of driver behavior, such as the preference to overtake on the left side or the tendency to return to the preferred lane after overtaking. The model completely ignores strategic lane change behavior, such as merging into traffic, moving to a preferred lane, positioning to the right lane for a forking highway and the preparation for exit.

Let us consider the issue of politeness as described in the model above. A driver might act politely towards cars which are trying to merge into the traffic from a merging lane which is shortly terminating. The same driver might aggressively pursue its goal of changing lanes when this is necessary for him to make the desired exit. The problem is not with the physical expression of the politeness, but with the fact that this politeness is modulated by higher level cognitive acts, which can not be modeled as forces.

3. STRATEGIC LANE CHANGE BEHAVIOR

Many highway simulation models assume that the lane change decision is based on a near-term optimization criteria. The vehicles will change lanes if they can get closer to their desired speed. This, of course is only true under the ideal assumption of an infinitely long highway, with no road signs or obstacles and drivers who have no preconceived ideas about the traffic lanes.

In a real world traffic, especially for highways traversing cities, however, there are a number of considerations which affect this behavior:

- **Entrances:** the drivers enter the highway on the rightmost lane which often serves as a temporary merging lane. The drivers need to merge into traffic before the lane ends.
- **Exits:** when drivers exit the highway, they need to position themselves to the appropriate exit lane (usually one or two rightmost lanes, but occasionally a leftmost lane). Depending on the traffic, the approaching maneuver must be started long before the exit.
- **Avoid the rightmost lane.** If the highway has more than two lanes, and there is a zone with many entrances and exits, then most drivers prefer not to drive on the rightmost lane, to avoid interference with cars entering and exiting the highway.
- **Leftmost lanes as high speed lanes.** The leftmost lane is usually deemed a high-speed lane and is avoided by vehicles which drive slower by choice or necessity (such as trucks). Vehicles which are pushing the posted speed limits, however, are preferring the leftmost lane.
- **Lane number variations.** The number of lanes on the roads changes with the location. Lanes terminate, new lanes are added in busy areas. The termination of lanes is usually signalled ahead.
- **High occupancy vehicle lanes.** Some highways designate the rightmost lane as a high occupancy vehicle lane. This would naturally be a preference for qualifying vehicles, but it also requires the traversal of many other lanes for entrance and exit.

Beyond the conditions imposed by the highway configuration, the lane change behavior also depends on the *strategies* of the individual drivers. Some drivers might try to reduce the number of lane changes, while others make them every time it might offer a short term advantage. Some drivers prefer to position themselves to the correct exit lane long time ahead, while others might wait to the last minute to move towards the exit. Some drivers prefer the leftmost lane, while others try to avoid it and prefer middle lanes.

In this paper we introduce a framework which models the static and dynamic lane preferences of the drivers. The framework integrates with the virtual physics based models described in the previous section - it does not replace but augments them. The preference model does not eliminate the optimization for the desired speed from the sources of driver decision. For instance, in an open highway with the planned exit far away, speed optimization might trump the preferences for certain lanes. When approaching the desired exit, however, positioning to a preferred lane gradually takes priority.

This agent-based model of traffic simulation allows us to study aspects of traffic which are impossible with previous models. Examples of the kind of questions we can answer are:

- Are highway exits which are close to each other a help or hinder to the smoothness of traffic?
- How does a left exit changes the shape of traffic?
- Do drivers which wait for the last moment to move for the exit lane help or hinder traffic? What about their performance (time to destination?) Their safety? Other's safety? Overall driving comfort?
- Do drivers who prefer the inside lane move faster?

We start by defining our notion of utility of a lane. The first idea would be to use the left hand side of Formula 6 as the utility metric. This value, however, can be negative: it's range is $[-C, C]$ where

$$C = (a + b_{max})\,(1 + p) \tag{9}$$

We need, however, a strictly positive utility metric for the further definitions. To achieve this, we add C to the formula. Thus the utility of the current, left and right lanes will be defined as:

$$\begin{aligned} U_c &= \Delta p_{th} + C \\ U_l &= (\hat{a}_i + p \cdot (\hat{a}_{j-1} + \hat{a}_{i-1}) - (a_i + p \cdot (a_{i-1} + a_{j-1})) + C \\ U_r &= (\hat{a}_i + p \cdot (\hat{a}_{h-1} + \hat{a}_{i-1}) - (a_i + p \cdot (a_{i-1} + a_{h-1})) + C \end{aligned}$$

The preference model modifies the virtual physics model by assigning the preference value $W_c \in [0.0, 1.0]$ to the lanes of the road. The preference values are assigned to the individual lanes based on a longer term planning process. The virtual physics model will consider the *weighted utilities* of the lanes $U_c^w = W_c \cdot U_c$ and so on.

This way, the vehicle might not move to a low priority lane even if that would confer a temporary advantage. Yet, the agent's behavior would still retain the smoothness associated with the virtual physics model. When all the lanes have the same preference, the behavior reverts to the basic virtual physics model.

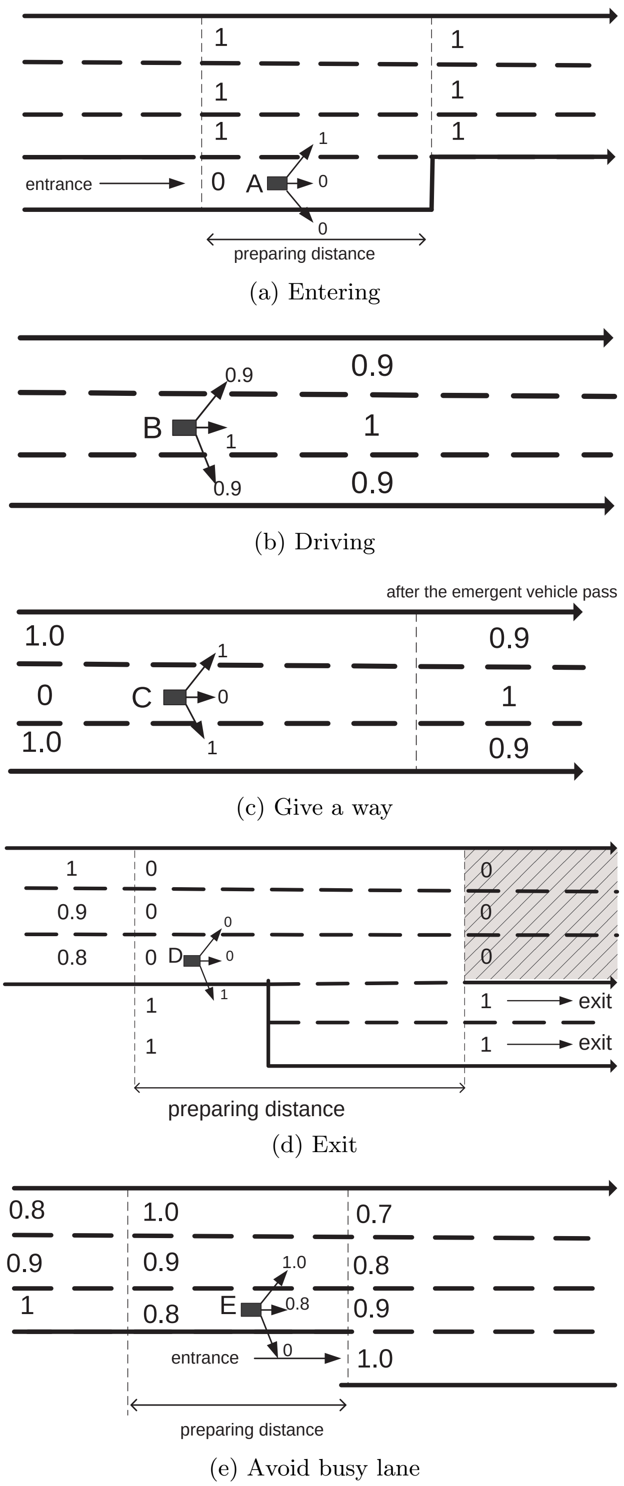
The preference weights are directly associated to the lanes of the highway, yet the vehicle needs to make decisions *one lane change at a time*. Thus the vehicle occasionally needs to accept a decrease in utility in order to reach a preferred lane after more lane changes.

To resolve this problem, we define the lane change preferences as follows. W_c is the preference of the vehicle's current lane. W_l and W_r are the *maximum* of all the preferences to the left and right of the vehicle, respectively.

Let's now consider some examples of the use of the preferences by the agent:

i) When *entering* the highway, the agent will set the preference of its terminating entrance lane to zero. This will cause it to move to the highway's continuing lanes as soon as it is safe (see Figure 2(a)).

ii) When *driving* on the highway, the vehicle will assign higher preference to the lanes it prefers driving on. The



(a) Entering

(b) Driving

(c) Give a way

(d) Exit

(e) Avoid busy lane

Figure 2: The agent tries to evaluate the preferences of lane changes.

preference gradients will be, however, milder. This allows the other components of the simulation to override this behavior, if significant advantage is to be gained - or if the tactical maneuver requires it (see Figure 2(b)).

iii) When the vehicle needs to *"give a way"* to a police car or emergency vehicle, it will set the specific lane(s) to zero preference, which will force it to move to one of the non-zero preference lane as soon as it is safe. Once the emergency vehicle has passed, the vehicle resets its lane preferences to the previous ones (see Figure 2(c)).

iv) If the vehicle prepares to *exit*, it will modify the lane preferences to prefer the exit lane. Note that this does not mean that the vehicle will immediately change to the exit lane, as a number of other safety conditions need to be satisfied for each lane change(see Figure 2(d)).

v) *Avoiding entering lanes.* Let us consider a vehicle which is on inter-city routes prefers to drive on the rightmost lanes. These lanes, however become extremely busy before and after exits with cars which are entering and exiting the highway. Thus many drivers prefer to the left side of the road around the exit to their default preferences after the merge finished. This shows in Figure 2(e). Note that this preference has again relatively mild gradient, and can be overwritten by other considerations.

3.1 Modeling lane changes under different conditions

The default virtual physics model assumes lane changes happened as the result of an *opportunity*. In real life, however, there are cases where the vehicle is *forced* to change lanes, even if the change doesn't improve the utility. For instance, the agent needs to give up its fast left lane in order to exit, or it needs to give way to an emergency vehicle.

These situations are modeled in our simulator by setting the preference of the current lane to zero. Even in these cases, although the vehicle wants to change lanes, it might not be able to, because the safety conditions will not be satisfied.

We define the *time to change lane* the amount of time between the moment when the weighted utility dictates a lane change until the moment when the lane change is safely accomplished. If the vehicle is not able to change the lane before the utilities are reversed (or the lane ends), we say that the vehicle *missed the lane change.*

To mimic the behavior of human agents in such situations, we introduced a *speed adaptation technique.* The safety condition for lane change is more likely to be satisfied if the vehicle modifies the speed such that it matches the one of the desired destination lane. Thus, under situations of *forced lane change*, the vehicle will change its desired speed to the current speed of the neighboring vehicle in the destination lane. If the vehicle needs to cross several lanes (as the case of the exit) it will change its desired speed in steps, always adapting it to the speed of the next destination lane. Once the forced lane change situation is terminated, the desired speed of the vehicle reverts to the one dictated by the virtual physics model.

4. A PROBABILISTIC MODEL OF SUCCESS FOR LANE CHANGES

Many drivers prefer to drive during most of the journey on the faster lane on the left side of the highway. To finish the journey, however, they need to exit from the rightmost lane. Thus, for most drivers, exiting the highway is a maneuver which requires several consecutive forced lane changes. In situations of heavy traffic, this can represent a significant safety risk.

Different drivers approach the problem of exit differently. Some prepare a long time ahead, moving towards the rightmost lanes. This, however, increases congestion on those lanes. Others remain on the fast lanes until the last moment – this however, requires several successive lane changes with very little room for error.

In this section, we describe in detail the considerations of preparation to exit, based on the lane change preference model introduced in the previous section. Similar considerations apply for the case when a vehicle needs to merge from a lane which soon will terminate.

Probability of successful lane change: The need to prepare in advance for exit is due to the fact that a driver who intends to perform a lane change might not be able to execute it for a certain amount of time.

The difficulty of the lane change depends on the local density of the vehicles in the target lane D_i and the average speed difference between the vehicle and the neighboring vehicles in the target lane ΔV_i. An experienced driver can estimate $Pr(t, D_i, \triangle V_i)$ - the probability that it can successfully change lanes in time t for a specific value of the density and speed difference. For the purpose of our simulation, we have collected this data by identifying lane change events in the simulator logs. The probability was extracted from the histograms of the time it took to actually perform the lane change.

Probability of successful exit If the vehicle is currently n lanes away from the exit lane, it will need to successfully execute n lane changes before exit. The driver needs to start its exit preparations at such a time / distance ahead so that it can successfully exit with a certainty (high probability).

In the rest of this paper we will use 90% for this probability value. This value requires some explanation, as it appears to be low: it would imply that 10% of the drivers will miss their exits. In reality, only a much smaller number of misses happen. What will happen in practice is that either (a) some of the other drivers will change their behavior such that they allow the vehicle to exit or (b) the vehicle will move even if the safety conditions are not satisfied. Note that case (b) does not immediately imply a crash, only a dangerous situation.

Let us now analyze how a driver can calculate the preparation time necessary for a safe exit with 90% certainty. Suppose we have $Pr(t_s, D_i, \triangle V_i)$- the probability of a single lane change which is finished at time t when the next lane i has density D_i and speed difference $\triangle V_i$. In general, if the agent tries to change from lane i to j in time n, the probability that it can succeed is

$$Pr(i,j,n) = \begin{cases} \sum_{t=1}^{n-(j-i)+1} Pr(t, D_{i+1}, \triangle V_{i+1}) Pr(i+1, j, n-t) & i < j \\ \sum_{t=1}^{n-(i-j)+1} Pr(t, D_{i-1}, \triangle V_{i-1}) Pr(i-1, j, n-t) & i > j \\ 1 & i = j \end{cases} \tag{10}$$

The probability of successful change across multiple lanes can be calculated through a recursive algorithm. As the probability of successful exit is monotonically (but not linearly) increasing with the time of exit preparation, we can find the minimum preparation time necessary to achieve any given successful exit probability through binary search in the space of calculated probabilities.

For a driver it is usually easier to tie the exit preparation to a specific distance to the exit rather than to a specific time to exit, as the current distance to the exit is usually easy to estimate from the information on the road signs. The "time to prepare" can be converted into "distance to prepare" by simply estimating the average speed of the vehicles on the lanes separating the vehicle from the exit lane.

Using these algorithms we can envision a fictional *optimal exit model.* This driver would first observe the relative speeds and densities in all the lanes which separate the vehicle from the exit lane. Then, using the calculations outlined above, the driver would be able to calculate the optimal time when it needs to start its exit maneuver (for a specific value of safe exit probability).

5. EXPERIMENTAL RESULTS

5.1 Simulation parameters

For the experimental study we have run experiments using our simulator which implements the virtual physics and agent models. The agent model also includes a number of tactical behavior components not discussed in this paper (such as communication through signaling), which ensures a higher accuracy and realism of the overall simulation. The experiments have been performed on a detailed, lane-by-lane model of a 22.13 mile stretch of Highway 408. Inflow and outflow information was acquired from the statistics of the expressway authority[1]. The vehicle inflow was modeled as a Poisson traffic, matching the specified average inflow rate. The statistical data, however, does not provide an explicit mapping between the point where a specific vehicle enters and leaves the highway. Thus, for our model, we choose exit points for the vehicle stochastically, with the probability that the vehicle entering at entrance i will have a destination at exit j being:

$$Pr(j) = \frac{Out(j)}{Out(j) + \sum_{k>j} Out(k) - \sum_{l>j} In(l)} \tag{11}$$

where $In(l)$ is the inflow rate of entrance with label l, and $Out(k)$ is the outflow rate of exit with label k. The denominator in the Equation 11 is the total number of vehicles which will pass or exit the location. However, the selection

[1]http://www.expresswayauthority.com/Corporate/ about-Statistics/HistoricalTraffic.aspx

Table 1: Default parameters of the simulation

Parameter	Symbol	Value
simulation step	Δt	$0.1s$
maximum deceleration	b_{max}	$5.0m/s^2$
vehicle length	x_{length}	$4m$
minimum distance	Δx_{min}	$2m$
acceleration	a	$1.5m/s^2$
desired deceleration	b	$2.0m/s^2$
headway time	T	$1.5s$
desired speed	v_0	$105km/h \pm 20\%$
politeness	p	0.5
politeness threshold	Δp_{th}	0.2
visibility range	$x_{visibility}$	$400m$
reaction time	T'	$0.4s$
lane change time	t_{lane}	$2.0s$

probability is calculated with the assumption that the vehicle doesn't exit before j, so we need to normalize them as

$$Pr(i,j) = \prod_{i<m<j} (1 - Pr(m))Pr(j) \tag{12}$$

To simulate the highway in the rush hour, we increase the inflow and outflow rate by the *flow ratio*. The parameters of the simulation are summarized in Table 1.

For the following experiments we will study two different types of vehicle behavior with the same virtual physics model but different agents. The SIG agent does not change the speed of the vehicle when trying to change lane. In contrast, the VAR agent is changing its desired speed to match the destination lane, according to the technique described in Section 3.1.

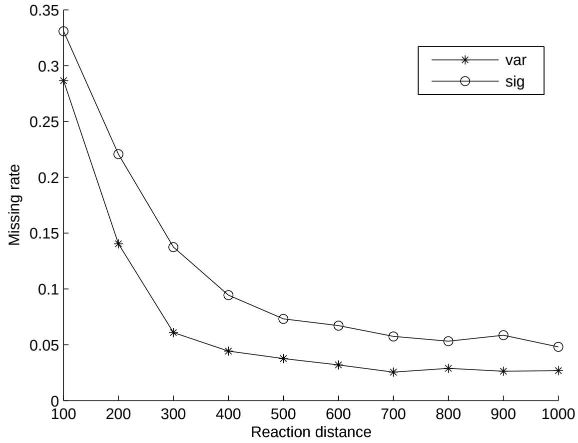
5.2 Rate of exit misses function of the exit preparation distance

In this experiment, we study the rate of the exit misses (or, in a different interpretation, of the dangerous exits) in function of the distance where the vehicles start their preparation for exit by changing their lane preferences to prefer the exit lane (as in Figure 2(d)).

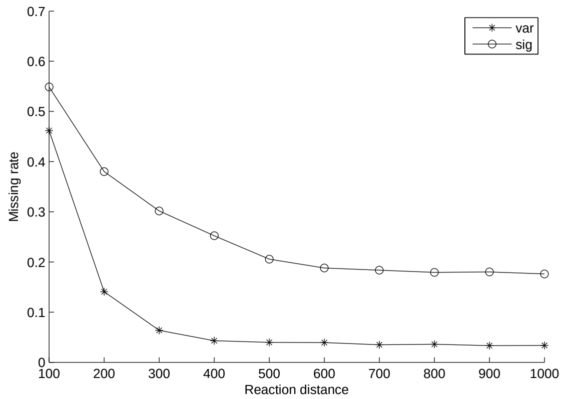
Figure 3(a) shows rate of exit misses for the two agents SIG and VAR for regular traffic on Highway 408. We find that for both agent types the miss rate decreases with the distance, but in general the VAR agent has a lower miss rate.

Figure 3(b) shows the same measurements for rush hour traffic (with the inflow and outflow increased five times). The conclusions from the normal traffic situation extend to this scenario as well. The rate of exit misses of the VAR agent did not change significantly, on the other hand the miss rate of the SIG agents is much higher, and it cannot be reduced below about 20% even with early preparation.

We conclude that the technique of adapting the speed to the target lane is a major component of safe driving under high traffic conditions. While this might appear as a common-sense advice for an experienced driver, it is an observation



(a) Normal



(b) Rush hour

Figure 3: The rate of exit misses function of the preparation distance with normal inflow and outflow rate 3(a), and during rush hour 3(b).

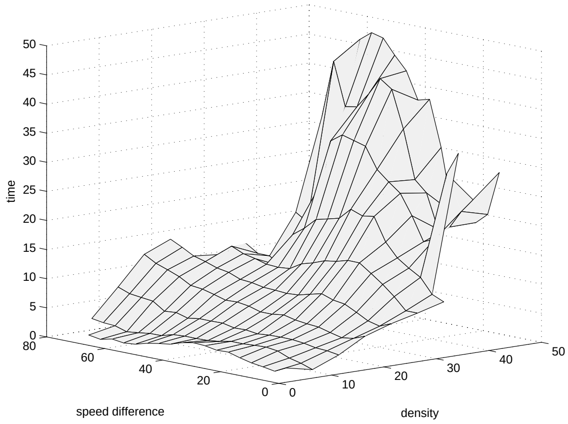
which does not appear in purely virtual physics based models, yet it emerges naturally when that model is augmented with an agent-based conscious behavior simulator.

5.3 Average lane change time

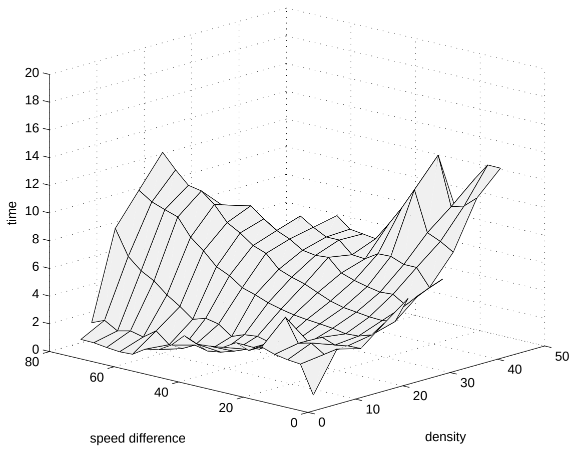
In this series of experiments we studied how long it takes for a SIG or VAR agent to perform a single lane change under various traffic situations. We assumed a very long preparation distance (1000m) and for each lane change forced by the strategic agent behavior we logged the traffic situation and the time to succeed t_s. Thus, the log does not contain the opportunistic lane changes dictated by the virtual physics model. To gather all possible local traffic situations, we run a set of simulations with different flow ratios.

In Figure 4(a) (SIG) and Figure 4(b) (VAR), we divided the density and speed difference into small ranges and plotted the average time to succeed function of density and speed difference.

The first conclusion we can reach from these graphs is that



(a) SIG



(b) VAR

Figure 4: Average lane change time for the SIG and VAR agent in various traffic situations.

both the speed difference and the density affect the time to change lanes. As expected, the time for the VAR agent is consistently shorter than for the SIG agent, reconfirming the validity of the speed adaptation strategy. For example, when the density is 30 vehicles per km, and the speed difference is 20 km/h, it takes 17.49s to do a lane change. However, if the agent adapts the desired speed, it only takes 6.94s to change a lane.

Another insight is that if the vehicle density is low, the speed difference has little effect on the lane change time, because the agent can simply let the high speed vehicle pass and change into the next lane before the new one comes. In the high density lane, however, as the speed difference increases, it needs to wait a long time before the safety condition is satisfied. On the other hand, with the same speed difference, the more vehicles in the agent's next lane, the more time it needs to take for a single lane change.

We conjecture that an experienced driver has an intuitive

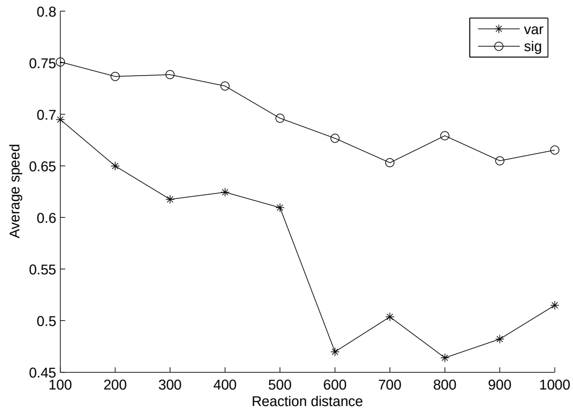


Figure 5: The average speed compared to the desired speed for arrived vehicles during rush hour on Highway 408.

understanding of the values of these graphs (choosing the graph which corresponds to his own driving style, SIG or VAR). What this means that given a specific traffic condition, the driver can estimate the time it will take to change lanes. This estimation will serve as input for the next experiment.

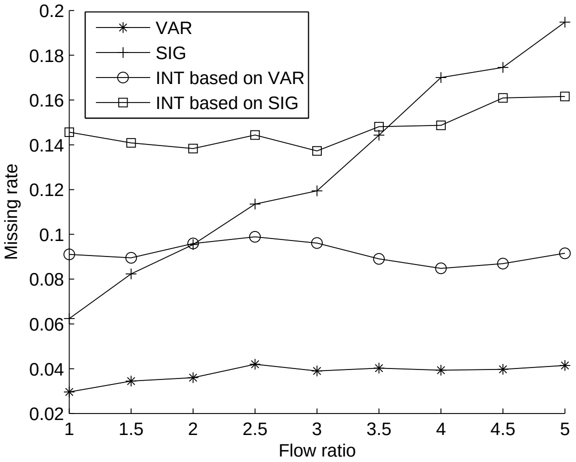
5.4 Adaptive preparation distance

It appears that the safest choice is to choose a VAR type agent as a sufficiently long preparation distance such that the risk of missing the exit is minimized. Unfortunately, such an agent would loose performance. Figure 5 shows the average speed for all arrived vehicles compared to their desired speed. The average speed of the VAR agent is significantly lower, which translates to longer trip times. Some of this is the unavoidable cost of safety. However, by maintaining the same preparation distance both under easy and difficult conditions, the agent is unnecessarily loosing performance.

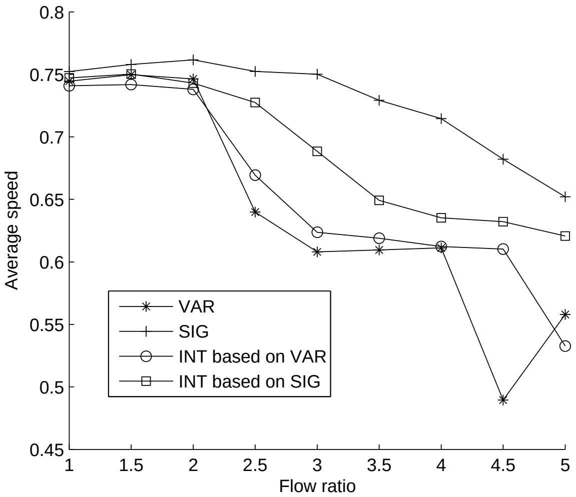
Figure 6 plots the missing rate as well as the averaged speed in the function of the inflow ratio. We compare four strategies: SIG and VAR with a fixed preparation distance of 600m, and their "intelligent" variants with adaptive preparation distance INT-SIG and INT-VAR. We find that, as expected, the adaptive strategies have a more "flat" diagram, allowing us to choose our preferred compromise between performance and risk.

6. CONCLUSIONS

Agent-based modeling can contribute significantly to the accuracy of microscopic highway simulations, in modeling the conscious behavior of the driver and the action of the automated driver aids. Yet, agent researchers need to thread carefully: we are contributing to a field with 50 years of history, with a collection of finely tuned models, which perform very well as long as their operational assumptions are maintained. There is little to be gained from insisting on a "pure" agent-based model. First, there are low level aspects of the driving which do not conform to the definition of an agent. Second, even if we manage to force our model into an agent straitjacket, we will need to reinvent the significant amount



(a) Rate of exit misses



(b) Average speed

Figure 6: The rate of exit misses and average speed in the function of flow ratio on Highway 408

of fine tuning which went into the virtual physics models. On the other hand, if we successfully integrate the virtual physics and agent models, the benefits are immediate.

This paper described an approach where the model of the conscious driver – representing the strategic thinking about lane preferences and planning for a safe exit – is integrated with and acts through the virtual physics model. We found that the model makes successful predictions on issues which are out of reach of the virtual physics based models. For instance, our model correctly predicts that the highest safety risk for exits appears at the case of moderate congestion, both low traffic cases and high congestion is comparatively more safe. This matches well with the results of studies of predicting crash prone situations for rear-end crashes [8] and lane-change crashes [7, 4, 1].

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