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Modeling the Strategic Behavior of Drivers for Multi-Lane Highway Driving

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Current state-of-the-art highway traffic flow simulators rely extensively on models using formulas similar to those describing physical phenomena, such as forces, viscosity, or potential fields. These models have been carefully calibrated to represent the overall flow of traffic and they can also be extended to account for the cognitive limitations of the driver, such as reaction times. However, there are some aspects of driver behavior, such as strategic planning, that are difficult to formulate mathematically. In this article, we describe the YAES-DSIM highway simulator, which integrates virtual physics models with an agent-based model. The virtual physics component models the physical vehicle and the subconscious aspects of the driver behavior, while the agent component is responsible for the strategic and tactical decisions, which are difficult to model using virtual physics. We focus on the lane change decisions of the drivers, with special attention to the optimal lane positioning for a safe exit. We have used the model to simulate the flow of traffic on Highway 408 in Orlando, Florida, and to study the impact of various tactical and strategic decisions on the efficiency and safety of the traffic.

Keywords Driver Behavior; Highway Simulation; Multi-Agent Simulation

INTRODUCTION

Many current microscopic traffic simulation models rely on mathematical formulas similar to those describing various physical phenomena: forces, viscosity, potential fields, and so on. We call these *virtual physics* models. Over the course of the last 50 years there was a gradual shift from formulas relying on fluid dynamics toward the individual treatment of the vehicle as a particle subject to a collection of forces. These models have been proved to predict well the integrative, long-term parameters of the traffic, such as throughput or average speed in congested traffic. However, these models are less successful in modeling the higher level cognition of the human driver and discrete decisions motivated by long-term, strategic considerations.

Our work is centered on improving the accuracy of microscopic highway simulation through agent-based modeling of the conscious aspect of driver behavior. The conscious part of the driver's behavior can be classified into strategic and tactical behavior. Strategic behavior involves decisions that 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, or matching the speed of the next line for easier lane change.

The majority of agent-based traffic simulator approaches assume that the complete behavior of the vehicle is represented by the agent. In contrast to this, our model chooses to retain the virtual physics based model as the best, most natural approximation of (a) the vehicle's real physics and (b) the highly learned driver behavior such as maintaining a constant speed or a constant distance from the leading vehicle. On the other hand, we argue that virtual physics-based models cannot conveniently represent conscious decisions that are discrete in nature, such as the choice to take a certain exit and the planning of the sequence of lane changes such that the vehicle reaches the exit lane in time. However, even if these decisions are taken at a higher

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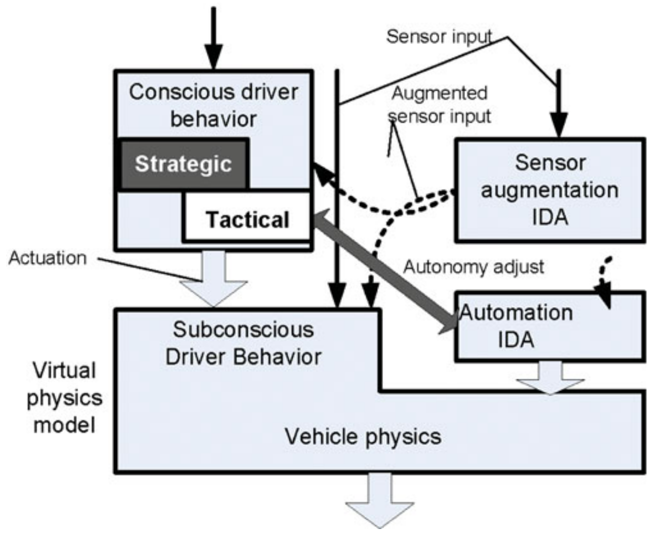


Figure 1 Overall architecture of the YAES-DSIM simulator.

level, the enactment of these decisions will happen through combinations of the same highly learned driver skills. Thus, in our model, the high-level decisions are enacted through the virtual physics model. At the same time, the low-level model must also inform the conscious component, for instance, by marking which decisions can be feasibly executed. In addition to the driver's conscious decisions, in modern vehicles, various automation techniques can also take control of the vehicle by either replacing or complementing the driver.

SIMULATOR ARCHITECTURE

The contributions of this article were implemented in the YAES-DSIM driver simulator based on the YAES (Bölöni & Turgut, 2005) modular simulator framework. The components of the simulator are divided into three classes as described in Figure 1.

The *virtual physics components* model the physics of the vehicle as well as those aspects of the driver that are either reflexive (such as emergency braking) or learned to the point of becoming subconscious (such as lane following and keeping a constant distance from the car in front).

The *agent component* 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 component will receive input from the environment (including sensor data, signaling data, and vehicle-to-vehicle and vehicle-to-infrastructure communication). The agent component acts through the virtual physics component, by temporarily changing its parameters.

The *intelligent driving assist components* (IDAs) model the action of various vehicle technologies that provide functionality beyond the basic vehicle control. Sensor augmentation IDAs improve the flow of information reaching the driver, and include night vision systems, blind-spot warning systems, surround-view cameras, and so on. In contrast, the automation IDAs directly contribute to the control of the vehicle. These components replace the virtual physics component with a separate control system. For instance, when the intelligent cruise control is turned on, it replaces the human driver's behavior completely and introduces its own vehicle-following rules. The transitions between the virtual physics and the automation component must model the real-world transition of control between driver control and automation. It has been shown that the appropriate choice of various automation technologies such as adaptive cruise control can improve the overall flow of the traffic (Kesting, Treiber, Schönhof, & Helbing, 2008); however, the level at which users are willing to accept these systems is an ongoing concern (Höltl & Trommer, 2013).

The contributions of this article focus on the model of the strategic behavior (the shaded area in Figure 1). For the starting point of the contributions described in this article see Luo and Bölöni (2010). However, we describe the majority of features provided by the simulator, albeit at a limited detail level. We use as our central example the planning for a safe exit from a congested highway that requires a number of lane changes. Realistic simulation of the circumstances in which lane changes occur is a practically important problem. It was found that about 10% of the crashes occurring on highways are sideswipe crashes, while about 11% of them are angle crashes (Pande & Abdel-Aty, 2006). Both types are associated with lane changes (the remainder of the crashes are mostly rear-end crashes).

The remainder of this article is organized as follows. The third section describes the virtual physics models that are the baseline of the contribution described in this article. The fourth section describes a number of functionalities provided by the agent component that complement the virtual physics model. The fifth section describes the model through which the agent's preferences for specific lanes are enacted. The sixth section discusses various strategies for exiting the highway. In the seventh section we describe a series of experiments of running YAES-DSIM to simulate the traffic of Highway 408 in Orlando, FL. Related work is discussed in the eighth section, and we conclude in the ninth section.

THE VIRTUAL PHYSICS COMPONENT

The virtual physics component of the YAES-DSIM simulator consists of a collection of models, selected such that they offer state-of-the-art accuracy in terms of the simulation dynamics; they are self contained, work well together, and extend the scope of virtual physics to as wide a range of behaviors as possible. The YAES-DSIM virtual physics model has three main components: a time-continuous car-following model, a lane-change model, and a human driver model.

The Car-Following Model

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 through a formula of the following general pattern:

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

where $\Delta x_i = x_{i+1}(t) - \Delta x_i(t)$ 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, Hennecke, & Helbing, 2000):

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

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

$$\delta(\mathrm{v_{i,}}\ \mathrm{v_i}) = \Delta\mathrm{x_{min}} + \mathrm{v_i T} + \frac{\mathrm{v_i}\ \mathrm{v_i}}{2\sqrt{\mathrm{ab}}}$$

where $\Delta\mathrm{x_{min}}$ is the minimum distance in case of congestion ($\mathrm{v_i} = 0$), T is the safe time headway that models the buffering time of the driver, and b is the comfortable deceleration, which cannot 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, $\mathrm{v_i} = 0$) to 0 (when the vehicle reaches its desired speed $\mathrm{v_i} = \mathrm{v_0}$). If a vehicle follows a leader with a negligible approaching speed ($\Delta v_i \approx 0$), the term $\mathrm{v_i T}$ in dominates such that the vehicle maintains a distance $\mathrm{v_i T}$ from the leader.

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

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

The car-following model defined in this way is collision free.

Lane-Changing Models

Lane changing is a discrete, binary choice of the driver. In his influential paper, Gipps (1986) proposed the following criteria for lane-changing decisions:

- Whether it is physically possible and safe to change lanes without an unacceptable risk of collision.
- The location of permanent obstructions.
- The presence of special purpose lanes such as transit lanes.
- The driver's intended turning movement.
- The presence of heavy vehicles.
- The possibility of gaining a speed advantage.

In later years, to these criteria researchers added the cooperation (or lack of cooperation) of other drivers and the driver's consideration toward the other vehicles on the road. This implies that systems must model not only the decisions of the lane-changing driver, but also the choices of nearby drivers. These decisions had been modeled through a wide range of approaches from rules expressed in a flowchart (Gipps, 1986), neural networks (Hunt & Lyons, 1994), fuzzy sets (Moridpour, Sarvi, Rose, & Mazloumi, 2012), and game theory (Kita, 1999).

The YAES-DSIM implementation extends the car-following model with the lane-change model described by Kesting, Treiber, and Helbing (2007), which models lane-change decisions and collaborative behavior through a calculation of utilities together with a simple threshold mechanism.

The model assumes that lane changes happen instantaneously: For a shift to the left lane, a vehicle that 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 cannot brake 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:

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

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 drivers is to achieve their desired speed, which implies a certain desired acceleration $\hat{a}_i$. At this point we assume that the only motivation of the driver to change lanes is to achieve this acceleration (which is not possible 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.

Kesting et al. (2007) calls *politeness* the degree at which a driver might consider the accelerations of the other vehicles as well when taking a decision to change the lane. Although throughout this article we use this parameter for a wider range of functionality, we retain the original name. The politeness parameter p specifies how much the driver discounts the other drivers' desired acceleration compared to his own. A value p = 0 indicates an impolite, fully selfish driver who does not care about other drivers (but still considers the safety criteria).

The vehicle i will decide to change the lane if the following inequality is verified:

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

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 into the lane. The intuition is that the vehicle favors changing the lane only when the advantage of the action is greater than the disadvantage it exerts to its neighboring vehicles. However, because the vehicle i cannot obtain the parameters (T, v_0, a, b) for its successors i – 1 and j – 1, the utility of lane change can only be calculated by the vehicle i's own parameters.

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.

The virtual physics model in YAES-DSIM implements several human driver features inspired from Treiber, Kesting, and Helbing (2006). First, we consider the fact that humans cannot perform an indefinite number of decisions per unit of time. This is modeled by restricting the driver to a single decision about acceleration in any given time step Δt. Thus, the driver can only change his mind about the acceleration $1/\Delta t$ times per second. This acceleration value will remain constant for the next interval Δt:

$$v_i\,(t + \Delta t) = v_i\,(t) + v_i(t)\Delta t$$

$$x_i\,(t + \Delta t) = x_i\,(t) + v_i\,(t)\,\Delta t + \frac{1}{2}\,v_i(t)\Delta t^2$$

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 the car-following equation the current state $(\Delta x_i, v_i, \Delta v_i)$ at time t – T'. If t – T' falls between two simulation steps at a distance $\beta\Delta t$ from the simulation step, the observation will be adjusted as:

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

COMPLEMENTING THE VIRTUAL PHYSICS MODEL

The agent component of the YAES-DSIM simulator is a collection of specific functional models that act through the virtual physics model. As the driving behavior of humans is a complex mix of tactics, strategy, reflex actions, communication, and sensing, the objective of these functional models is to simulate as many aspects of the driving behavior as possible. The main topic of this article, the strategic behavior, is only one of these additional functionalities. In the following we succinctly present some of the functional models that directly interact with the strategic lane change behavior:

- The visibility model: the way in which the driver becomes aware of other vehicles and obstacles.
- The communication model: the ways in which the drivers of the vehicles communicate with each other.
- The reflex action model: the ways in which the drivers take fast actions that are not covered by the virtual physics model, which operates more "smoothly." Examples include the details of a lane change, including ability to abort a started lane change, quick swerving to avoid an accident, and so on.

The Visibility Model

Virtual physics models posit forces of attraction and repulsion toward the surrounding vehicles and obstacles. In the real world, these virtual forces are enacted through the actions of the driver, which implies that only the vehicles of which the driver is aware will be considered. In fact, the main way in which the collision-free property of a virtual physics model might break down is the case when the driver is not aware of a nearby vehicle.

The visibility model of YAES-DSIM allows us to specify the distance at which the driver considers surrounding vehicles and takes into consideration the occlusion of visibility by large vehicles. Furthermore, we can model limited visibility conditions, such as fog and rain.

The visibility model interacts with the other components of the simulator in several ways. The default assumption is that of *sufficient visibility*: The driver assumes that consideration of the currently visible vehicles is sufficient input to the rest of the simulator (the virtual physics and higher level components).

There are, however, situations when the driver is aware that his visibility is reduced, and he needs to take this into account in both the low-level driving and high-level plans. In some situations, these plans are influenced by changeable message signs and variable speed limit displays (Hassan, Abdel-Aty, Choi, & Algadhi, 2012). Although the response to low visibility is distributed throughout the system, YAES-DSIM deploys the technique of *virtual objects,* which allows us to modify only the visibility model to create the response to low-visibility situations. Virtual objects are entities not present in the physical reality, but that are added to the conscious sensing of a given driver. For instance, if a human driver practices *defensive driving* the driver will assume the existence of virtual objects just outside of their current visibility boundaries—for instance, behind large vehicles or at the limit of the visibility distance.

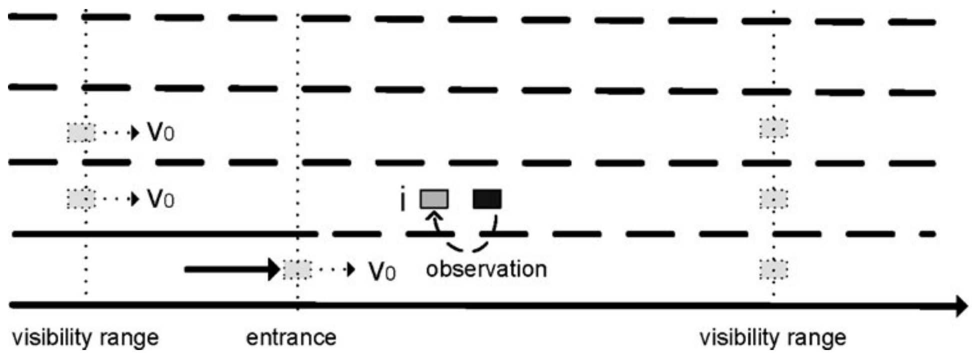


Figure 2 Augmentation of the visibility model for defensive driving under reduced visibility conditions. Solid border gray rectangle: the considered vehicle. Black rectangle: physically sighted vehicle. Dotted border rectangles: virtual vehicles considered by the driver model.

Figure 2 shows the complex situation of a driver who is driving in the rain near the highway entrance on the rightmost lane. The driver is aware of her distance-limited visibility and the lack of visibility toward the vehicles entering the highway. The defensive driving strategy of the driver considers the existence of six virtual objects: three immobile vehicles at the outer range of her forward visibility, two moving vehicles at the outer range of her backward visibility, and one moving entering vehicle. The driver will not need to consider vehicles that are more than one lane away. Note that defensive driving does not necessarily imply a low speed—in this particular situation a sudden brake will be just as bad as an excessive speed. Overall, however, this technique correctly models the slowdown of the overall traffic in the situation when the visibility distance decreases. Furthermore, as the visibility model can be configured from vehicle to vehicle, we can model the natural mix of defensive and aggressive drivers.

Communication Model

Vehicles on the highway communicate with each other through various implicit and explicit means. The importance of communication from the point of view of the driver is that it allows him to form a better model of the other vehicles in the traffic.

The term *communication* here includes both the traditional communication models (such as brake lights and turn signals) and the emergent electronic communication models (vehicle-to-vehicle [V2V] and vehicle-to-infrastructure [V2I]). Both of them affect traffic by transmitting information about the observations, actions, and plans of the vehicles to another vehicle. Naturally, there can be differences concerning the propagation range, speed, and the type of information transmitted. For instance, brake lights improve the precision of the driver's assessment of the lead vehicle's speed and deceleration. A V2V collision warning system might transmit exactly the same information as the brake lights, but it might do so over the span of several vehicles. Some communication techniques are enforced by law (such as signals), while others are informal and sometimes even illegal (such as "pressing" a vehicle from behind to force it to accelerate).

From the point of view of the main subject of this article, lane-change behavior, it is important to model the directional signals. Directional signals affect the overall traffic because they can significantly decrease the probability of a lane-change accident due to insufficient knowledge.

To effectively implement the logic of direction signals, we need to disconnect the decisions of *lane change favoring* and *lane change safety*. In the YAES-DSIM implementation, if the lane change favoring condition is satisfied, the agent will start signaling the lane change. After 3 s, the agent will start checking the lane change safety. If the lane change is perfectly safe, the agent will perform the lane change, which will take about 2 s to complete. If the safety condition is not fully satisfied, the agent might also take a risk action (R), which means initiating the lane change under the assumption that the vehicles on the new lane will take appropriate actions to avoid collision. If the agent is not willing to take a risk, it can continue signaling and maintain its current speed (O), it can abandon signaling and declare a lane change failure (S), or it can try to change its speed in the positive or negative direction (C+ or C–) to obtain a more favorable lane change safety value.

A signaling vehicle is registered by the visibility model of the other vehicles and it might change the driving behavior of these vehicles. In principle, the model uses the same virtual object model as the reduced visibility models already discussed. However, the drivers also need to make some discrete choices, depending on their willingness to give way or their guess on what the signaling vehicle will do next. A courteous driver will consider a virtual that which models the signaling vehicle's new position as if the lane change already happened. This will force the other components of the model to give space to the virtual vehicle, facilitating the safety condition of the signaling vehicle. A not courteous driver will simply not consider the virtual vehicle.

A simple situation is presented in Figure 3, where vehicle V2 might or might not consider the signal by vehicle V1. Even in such a relatively simple situation, a number of discrete choices exist. A courteous V2 driver would slow down (C–), or take a

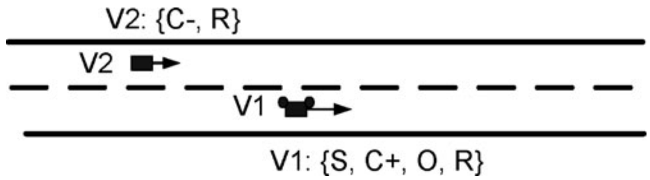


Figure 3 Single-vehicle lane change with signaling.

risk (R) of colliding with vehicle V1 if that takes the choice to change lanes without the safety condition being satisfied. On the other hand, vehicle V1 has several choices: to take the risk and move (R), to continue signaling while maintaining speed (O), to increase speed (C+), or to stop signaling and declare failed lane change (S). In the case of a failed lane change, the vehicle will wait for a certain time before trying again. The justification behind the desire to change lanes might affect the discrete choices of the vehicles—for instance, if the vehicle wants to change lane in order to improve its speed, is will be less likely to take a risk compared to the situation where the lane is ending (forced lane change).

The combination of various action choices is especially problematic when two or more vehicles signal lane changes simultaneously, such as in the example in Figure 4. The dilemma is especially difficult for vehicle V2, for whom a decision to increase the speed (C+) would reduce the risk of its own lane change; however, courteousness toward V1 would require a decrease in speed (C–). The current implementation of YAES-DSIM makes conservative choices in such situations.

Reflex Action Model

The lane-change model (Kesting et al., 2007) used in the virtual physics component of YAES-DSIM shares with many similar models the property that lane changes are instantaneous: a vehicle appears in the neighboring lane and disappears from the current lane at the same time. The new following car will need to hit the brakes at the very instant when this movement happens. In practice, cars change lanes along a diagonal lane, over a period of time t_{lane} (see Figure 5). At the moment when the lane change starts, all the following vehicles will know the intention of the driver, and they will react accordingly. To drive safely, the followers on the destination lane need to act as if the lane change has been completed as soon as it starts. On the other hand, the followers on the source lane act as if the

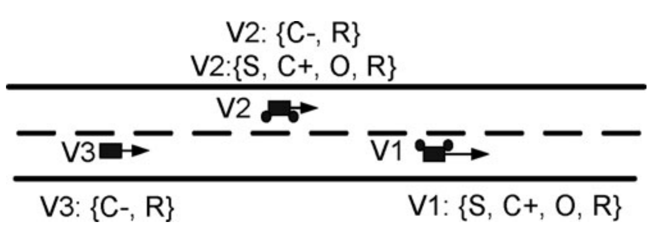


Figure 4 A more complex lane-change scenario. Two vehicles signal intentions of lane change.

car is still on their lane until the completion of the maneuver. This caution is justified by the fact that the cars can, indeed, abandon a lane change in the middle of the maneuver. We can model this pessimistic reaction by making the assumption that during the lane-change maneuver the vehicle occupies both lanes.

This model has implications for the car following and lane-changing model. In Figure 6, at time t, agent i tries to evaluate the decision of the left change based on the observation at $t - t_{sense}$. Behind itself, the agent observes an accident so it considers no follower in the original lane. On the left, the agent finds no vehicle, but a vehicle two lanes left is changing to the right. So the new follower in the target lane should be vehicle k – 1. There are several possible new leaders in the target lane: vehicle k + 1, j + 1, or i + 2. In general, the agent should consider all the vehicles in the target lane, as well as all the vehicles moving toward the target lane. In this example, the new leader should be vehicle k + 1 as it is the nearest vehicle in the target lane.

To model the cognitive limitations of human drivers, we do not allow a vehicle to decide on a second lane change during the time it is engaged in the first. During the lane change, the agent can only control the acceleration of the vehicle. The new accelerations are calculated based on the predicted leader on the destination lane.

This behavior is sometimes explicitly recommended by driver's manuals. For instance, the official driver's manual in California specifies that lane changes must be done "one at a time." While aggressive drivers occasionally do perform multiple-lane changes, such occurrences are rare.

Let us consider a situation when two vehicles, driving in parallel on the left and right lanes of a three-lane highway, simultaneously make the decision to move to the middle lane. This leads to an accident under all the models discussed previously. In real life, however, such situations rarely lead to accidents, because the drivers will become aware of the other driver's intentions by observing the other vehicle's diagonal path. Seeing the dangerous situation developing, one or both drivers abandon the lane change and remain in (or return to) their previous lanes. Thus, the lateral movement of the vehicles acts as an implicit communication signal. Naturally, if the vehicles are using their directional signals, the message can be transmitted before the lane change had started.

The YAES-DSIM simulator implements this communication model by creating virtual objects for the diagonally moving vehicles both in the starting lane and in the destination lane. This allows us to use the virtual physics model unchanged both for the drivers in the start lane, who consider the lane change finished only when the lead vehicle has completely moved to the new lane, and the vehicles in the destination lane, who consider the lane change as soon as the vehicle starts to move along the diagonal. With this model, it is possible for the virtual physics model to indicate a collision, which, however, is only a potential one. In this case the vehicles can still take a reflex action to avoid the collision by canceling the lane change.

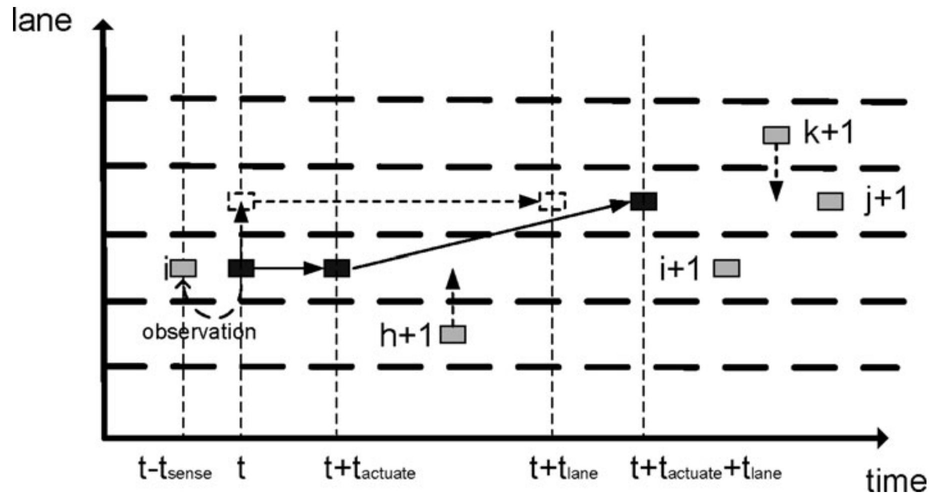


Figure 5 The sensing and actuation delays for a driver agent making a decision at time *t*.

STRATEGIC LANE CHANGE BEHAVIOR

Many highway simulation models assume that the lane-change decision is based on a near-term optimization criterion: for instance, that the vehicles will change lanes only if they can get closer to their desired speed. This is a realistic assumption if there are no exits and entrances nearby, there are no road signs or obstacles and the drivers have no preferences for specific traffic lanes. In real-world traffic, however, especially for highways traversing cities, there are a number of additional considerations affecting lane-change 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 that drive more slowly by choice or necessity (such as trucks). Vehicles that are "pushing" the posted speed limits, however, prefer the leftmost lane.
- *Lane number variations.* The number of lanes on the roads changes with the location. Lanes terminate, and new lanes are added in busy areas. The termination of lanes is usually signaled ahead.
- *High-occupancy vehicle lanes.* Some highways designate the rightmost lane as a high-occupancy vehicle lane. This would

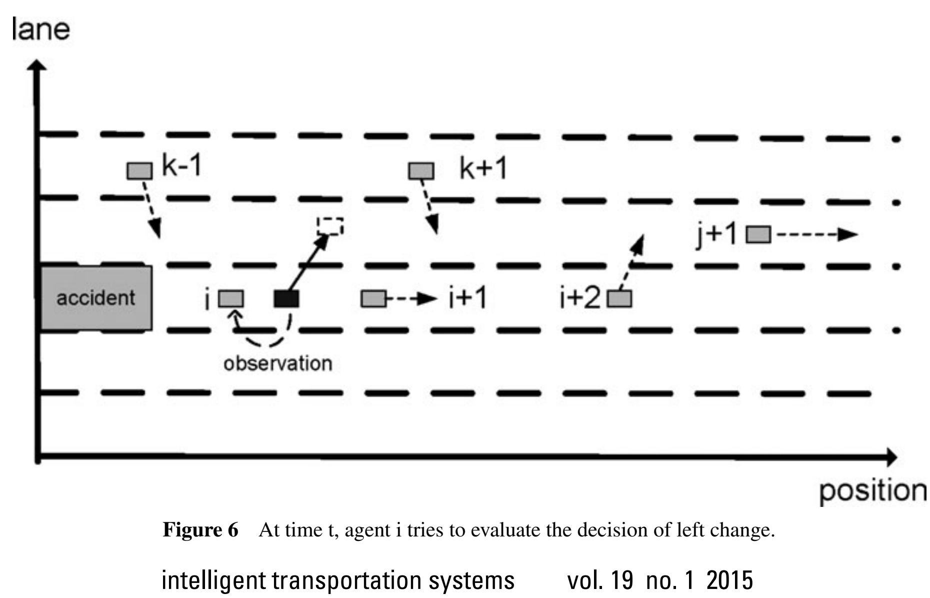


Figure 6 At time t, agent i tries to evaluate the decision of left change.

naturally be a preference for qualifying vehicles, but it also requires the traversal of many other lanes for entrance and exit.

There are also other situations where the lane change must be performed under special rules, such as at toll plazas (Al-Deek, Mohamed, & Malone, 2005). 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 offers a short-term advantage. Some drivers prefer to position themselves to the correct exit lane a long time ahead, while others might wait until the last minute to move toward the exit. Some drivers prefer the leftmost lane, while others try to avoid it and prefer middle lanes.

The agent-based strategic module of the YAES-DSIM simulator models the static and dynamic lane preferences of the drivers. The strategic module operates together with the virtual physics component and the other functional components. The strategic preference 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, moving to the exit lane gradually takes priority.

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

- Are highway exits that are close to each other a helping or hindering factor to the smoothness of traffic?
- How does a left exit change the shape of traffic?
- Do drivers who wait for the last moment to move to the exit lane help or hinder traffic? What about their performance (time to destination), their own and the other drivers' safety, and the overall driving comfort?
- Do drivers who prefer the inside lane move more quickly?

We start by defining our notion of *utility of a lane* from the point of view of a driver. The first idea would be to use the left-hand side of the formula for lane change utility as the utility metric. This value, however, can be negative: Its range is *[–C, C]* where:

$$C = (a + b_{max})(1 + p)$$

We need, however, a strictly positive utility metric for 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:

$$U_c = \Delta p_{th} + C$$

$$U_l = (\hat{a}_i + p \cdot (\hat{a}_{j-1} + \hat{a}_{i-1})) - (a_i + p \cdot (a_{i-1} + a_{j-1})) + C$$

$$U_l = (\hat{a}_i + p \cdot (\hat{a}_{h-1} + \hat{a}_{i-1})) - (a_i + p \cdot (a_{i-1} + a_{h-1})) + C$$

The preference model modifies the virtual physics model by assigning the preference weight $W_c \in [0.0, 1.0]$ to the lanes of the road. The preference weights 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:

1. 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 (Figure 7a).
2. When *driving* on the highway, the vehicle will assign higher preference to the lanes it prefers driving on. The 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 (Figure 7b).
3. When the vehicle needs to "*give 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 nonzero preference lane as soon as it is safe. Once the emergency vehicle has passed, the vehicle resets its lane preferences to the previous ones (Figure 7c).
4. 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 (Figure 7d).
5. *Avoiding entering lanes*. Let us consider a vehicle whose driver usually prefers the rightmost lanes. These lanes, however, are extremely busy before and after exits with cars that are entering and exiting the highway. Thus, many drivers prefer to move away from the rightmost lane when the highway traverses a city. This situation is shown in Figure 7e. Note that this preference has a relatively mild gradient, and can be overwritten by other considerations.

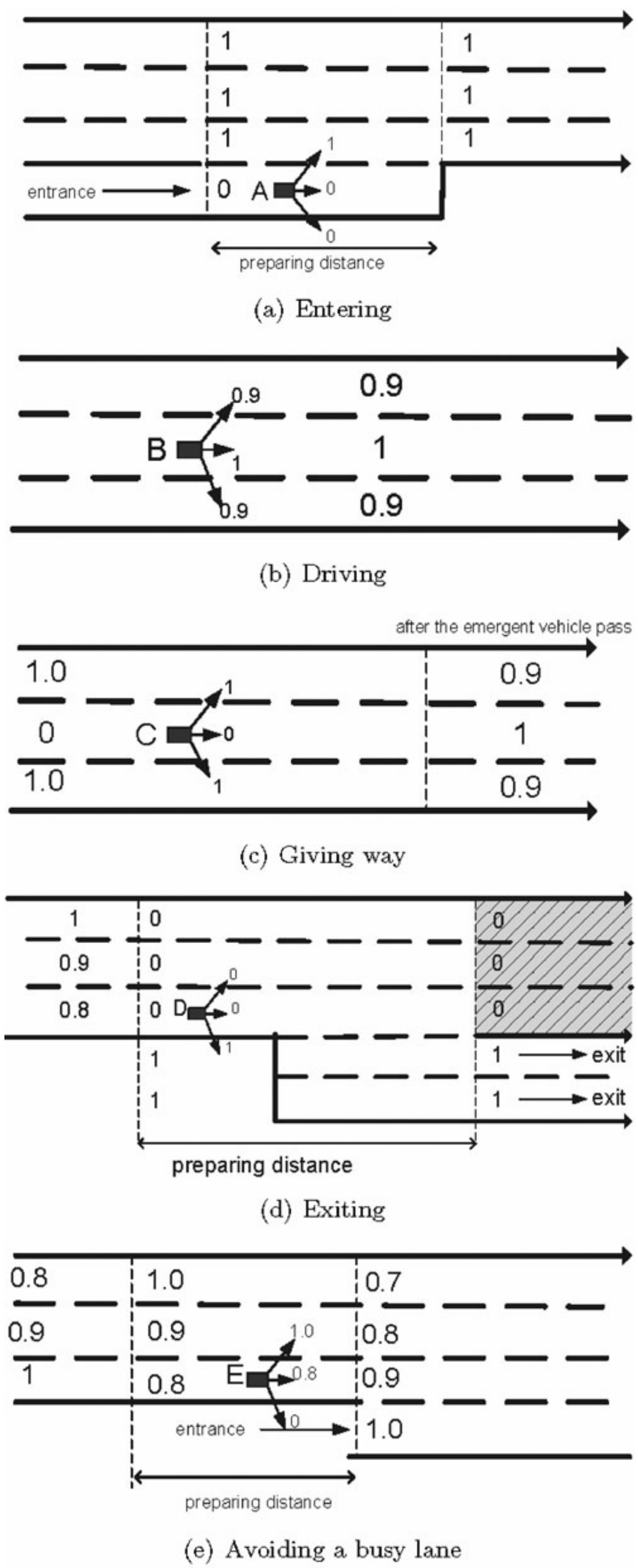


Figure 7 Lane preferences for various traffic situations and tactical goals of the agent.

Specific Situations

Although the framework as already discussed is quite generic, the agent must also consider a series of specific situations when making strategic decisions. For instance, the agent must consider whether a lane change is *optional* or *forced*. A lane change dictated by a judgment that in the new lane the driver can approximate better his own preferred speed is optional (this is a lane change motivated by the formula of lane change utility). In this case the current lane will still have a nonzero preference weight $w_{current}$. For an optional lane change the vehicle will still consider the option of staying in the current lane.

The alternative case is a forced lane change, where the preference weight of the current lane is zero $w_{current} = 0$. A forced lane change might happen when the vehicle wants to exit, when the current lane ends, or when special conditions arise, such as the necessity to avoid an accident vehicle or to give way to an ambulance or firefighter. Even in forced lane changes, the vehicle is not be able to change lanes if the safety conditions are not satisfied.

If the lane change cannot take place before the critical condition triggering the forced lane change happens, we say that the lane change *failed*. A failed lane change can correspond to a number of different real-world outcomes:

1. The vehicle is forced to move out to the highway shoulder and comes to a complete stop.
2. The neighboring drivers, noticing the difficult situation of the vehicle, take exceptional actions to let the vehicle make the lane change in safety. This requires the drivers to temporarily ignore their own utility and preferences.
3. The vehicle takes a risk and makes the lane change when the safety considerations are not fully satisfied. Due to the reflex evasive actions of the drivers (breaking, acceleration, swerving), the accident is avoided.
4. The vehicle takes a risk, makes the lane change and gets into an accident.
5. (If possible) The vehicle changes its plans, for instance, by taking the next exit.

Simulating which one of these outcomes will happen would require a completely new level of modeling detail, which includes the modeling of reflex actions and precision driving skill of the drivers, as well as their ability to think under pressure. Thus, our model can only predict the occurrence of a dangerous lane change, but cannot decide whether an accident actually happened or had been narrowly avoided.

Lane Change Tactics

Finally, we need to discuss about the tactical aspects of a lane change. Once a driver decides on a lane change, he needs to wait for the moment when the safety conditions are satisfied. We consider two different tactics that the agent might deploy:

The source lane speed tactic. The agent continues to move with the speed calculated according to the virtual physics models of the source lane, while continuously checking whether the lane change safety condition is satisfied. Essentially, the agent keeps driving as before. When the safety condition is satisfied, the vehicle initiates the lane change. A failed lane change is declared if the safety condition does not become satisfied within a deadline.

The destination lane speed adaptation tactic. The agent tries to match the speed of the lead vehicle in the destination lane, while maintaining the safe following distance on the source lane. Thus, the agent tries to move as if it would already be on the destination lane, with the hope that this speed adaptation might make it more likely that the lane change safety condition will be satisfied. In YAES-DSIM this tactic is implemented by overriding the virtual physics speed control technique except the current lane's safety condition. Note that it is not always possible to match the speed of the destination lane if the destination lane moves faster than the source lane. Conversely, the speed adaptation tactic might require the driver to move more slowly than what would be possible on the source lane. If the vehicle needs to cross several lanes (as in 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 its own preferences. As in the case of the source lane speed tactic, if the safety condition is not satisfied within a deadline, a failed lane change is declared.

HIGHWAY EXIT STRATEGIES

Many drivers prefer to spend 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, a maneuver that requires several consecutive forced lane changes. In situations of heavy traffic, this can represent a significant safety risk.

Drivers can use a number of different strategies for highway exits. These strategies impact not only their personal success rate, but also the general shape of the traffic. A cautious driver will start moving toward the rightmost lane a long time before the exit. This, however, increases congestion on the rightmost lanes. A more aggressive strategy would be to stay on the fast lanes as long as possible—this, however, requires several successive lane changes with very little room for error, and possibly the need for reflex actions from the other drivers.

The YAES-DSIM simulator builds the model of the highway exit strategy on top of the lane change preference model introduced in the previous section. The driver needs to set the preference weights on the various lanes in such a way that (a) it will reach the exit on the rightmost lane and (b) other desired properties are satisfied, such as safety, politeness, and desired speed.

We consider two different strategies.

The *static schedule exit strategy* approach assumes that the driver changes the preferred lane at fixed distances from the exit. For instance, the driver might choose to be no farther than on lane 3 by 600 m from the exit, lane 2 by 400 m and lane 1 when 200 m from the exit. Aggressive and cautious strategies can be modeled through the variation of these distances and the relative lane preferences within the sections. The placement of exit notification signs on the highways often provides anchor points for these preference segments.

Using the *adaptive exit strategy* the drivers change their lane preferences as a function of current traffic situation. They start their move toward the exit lanes earlier if there is dense traffic that makes lane changing harder. On the other hand, in light traffic, an adaptive driver might stay in the fast lanes to locations much closer to the exit.

YAES-DSIM models the adaptive exit strategy by developing a probabilistic model of lane change success. Strictly speaking, traffic is not probabilistic in YAES-DSIM—the validity of the probabilistic strategy is justified by the specific driver's uncertainty about the intentions and strategies of other drivers.

We assume that every driver, based on her historical experience with traffic conditions, can develop a probabilistic model of the success of the lane changes. The two parameters of this model are 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 $\Pr(t, D_i, \Delta V_i)$—the probability that the driver 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.

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 exit preparations at such a time/distance ahead so that the driver can successfully exit with a high probability. In the rest of this article we use 90% for this probability value. Note that this does not mean that 10% of the drivers will miss their exits, but that for about 10% of the exits this will not be performed in guaranteed safety.

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

$$\Pr(i, j, n) = \begin{cases} \sum_{t=1}^{n-(j-1)+1} \Pr(t, D_{i+1}, \Delta V_{i+1}) \cdot \Pr(i+1, j, n-1) & if\, i < j \\ \sum_{t=1}^{n-(j-1)+1} \Pr(t, D_{i-1}, \Delta V_{i-1}) \cdot \Pr(i+1, j, n-1) & if \quad i > j \\ 1 & if \quad i = j \end{cases}$$

The probability of successful change across multiple lanes can be calculated through a recursive algorithm. As the


```
0 2 start 6986
500 3 right entrance:ColonialDrive;Titusville:1310
600 2 right merge
1100 3 right entrance:ColonialDrive;Titusville:3493
1200 2 right merge
3700 3 right entrance:AlafayaTrail:13640
3750 2 right merge
4900 3 right entrance:RouseRoad:3530
5250 4 right extend
5300 3 right exit:RouseRoad:730
6800 2 right exit:DeanRoad:1150
7500 3 right entrance:DeanRoad:5780
```

Figure 8 Map of the first 7.5 km of the modeled highway stretch and its description in the specification language of YAES-DSIM.

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. The driver first observes the relative speeds and densities in all the lanes that separate the vehicle from the exit lane. Then, using the calculations just utlined, the driver would be able to calculate the optimal time when it needs to start his exit maneuver (for a specific value of safe exit probability).

To put these two strategies in context, we need to mention that in general, driving schools and manuals recommend a static schedule exit strategy. For instance, a driving school's website recommends a fixed distance ($\frac{1}{2}$ mile) for the exit preparation. However, the official driver's manuals are much more vague. The New York state driver's manual requires you to get into the exit lane "well ahead of time," which allows the possibility of adaptation. To further complicate this, Web forums show anecdotal evidence for traffic police stopping people for too late merging. On the other hand, the Minnesota state driver's manual explicitly recommends late merging. Our personal experience and discussion with traffic experts suggests that many drivers perform some level of exit optimization.

RESULTS OF EXPERIMENTS

Map Representation

The experiments have been performed on a detailed, lane-by-lane model of a 22.13-mile stretch of Highway 408 in Orlando, FL. Figure 8 shows the map of a 7.5-km stretch at the beginning of Highway 408 and its description in the specification language of the YAES-DSIM simulator. The language maps the two-dimensional (2D) geographic coordinates of the highway into a one-dimensional strip (this information can be converted back to a 2D map format for visualization purposes). However, the language allows an exact specification of the configuration of the highway lanes over every segment of the road, as well as the ways in which lanes flow into others, are started, merged, split, and terminated. Thus, the specification creates an exact model of the number and location of lane changes a driver must perform.

Simulation Parameters

The experimental study had been performed using the YAES-DSIM simulator, implementing the virtual physics models described in the third section and the agent-based functionality described in the fourth, fifth, and sixth sections. The experimental scenario for the arrival and exit information has been created as follows. Inflow and outflow information was acquired from the statistics of the Orange County Expressway Authority.

The vehicle inflow was modeled as a Poisson traffic, matching the specified average inflow rate. The statistical data, however, do not provide an explicit mapping between the point where a specific vehicle enters and the point where it leaves the highway. Thus, for our model, we choose the exit point for each vehicle stochastically, with the probability that the vehicle entering at entrance i will have a destination at exit j being:

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

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 is the total number of vehicles that will pass or exit the location. However, the selection probability is calculated with the assumption that the vehicle doesn't exit before j, so we need to normalize this as:

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

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 all the graphs that follow, the simulation was run for a single span of 1 h (36,000 simulation steps) per data point. However, the experimental results were always computed over all the vehicles in the traffic for the span of the simulation as either a mean (for lane change time) or a percentage (for rate of risky exits).

Table 1 Default parameters of the simulation.

Parameter	Symbol	Value
Simulation step	Δt	0.1 s
Maximum deceleration	b_{max}	5.0 m/s^2
Vehicle length	x_{length}	4 m
Minimum distance	Δx_{min}	2 m
Acceleration	a	1.5 m/s^2
Desired acceleration	b	2.0 m/s^2
Headway time	T	1.5 s
Desired speed	v_0	105 km/h $\pm$ 20%
Politeness	p	0.5
Politeness threshold	Δp_{th}	0.2
Visibility range	$x_{visibility}$	400 m
Reaction time	$T\prime$	0.4 s
Lane-change time	t_{lane}	2.0 s

In the following experiments we use two agent types differentiated by their use of the lane-change tactics:

- SIG agents: Implement the virtual physics model as described by the third section, in combination with the agent based components described in the fourth section, and the strategic lane change behavior and the source lane speed tactic described in the fifth section. The highway exit strategy used was the static schedule with 600 m total preparation distance as described in the sixth section.
- VAR agents: Implement all the functionality of the SIG agents, but use the destination lane speed adaptation tactic described in the fifth section.

Rate of Risky Exits Function of the Exit Preparation Distance

In this experiment, we study the rate of the risky exits (in the sense discussed in the fifth section) as a 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 7d).

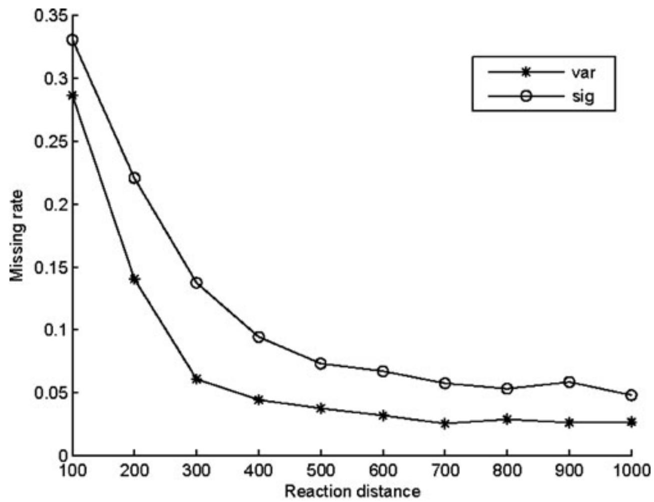
Figure 9a shows the rate of risky exits for average traffic density on Highway 408. We find that for both agent types the risky exit rate decreases with the preparation distance, but in general the VAR agent has a lower risky exit rate.

Figure 9b shows the same measurements for rush-hour traffic (with the inflow increased five times). The conclusions from the normal traffic situation can be applied to this scenario as well. The rate of risky exits of the VAR agent did not change significantly; on the other hand, the risky exit rate of the SIG agents is much higher, and it cannot be reduced below about 20 even with early preparation.

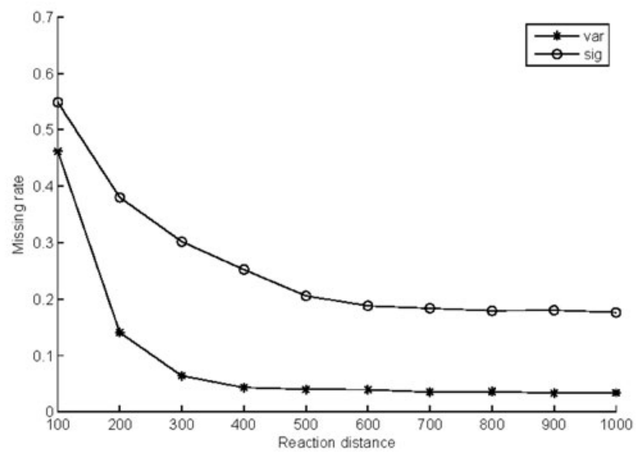
We conclude that the destination lane speed adaptation tactic is a major contributor to safe driving in dense traffic. While this might appear as commonsense advice for an experienced driver, it is an observation that does not appear in the virtual physics models presented in the third section, yet it emerges naturally when that model is augmented with an agent-based conscious behavior simulator.

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 (1000 m), 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.



(a) Normal



(b) Rush hour

Figure 9 The rate of risky exits function of the preparation distance (a) with normal inflow and outflow rate and (b) during rush hour.

In Figure 10a (SIG) and Figure 10b (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 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 destination lane speed adaptation tactic. For example, when the density is 30 vehicles/km, and the speed difference is 20 km/h, the SIG agent takes 17.49 s to do a lane change, while the same value for a VAR agent is only 6.94 s.

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 case of high traffic density, however, as the speed difference increases, the vehicle needs to wait a longer time before the safety condition is satisfied. Similarly, for a given speed difference, the more dense the traffic, the longer it takes to change the lane.

Although it appears that the time to change shows a drop for values of high traffic density and high speed difference, what actually happens here is that under these circumstances many lane change events fail (i.e., they could not be accomplished in 1000 m). The failed events are not counted in these graphs.

Impact of the Adaptive Highway Exit Strategy

In the next series of experiments, we studied the impact of the adaptive highway exit strategy as discussed in the sixth section. We compared four strategies: SIG and VAR with a static schedule exit strategy of 600 m, and their variants with adaptive exit strategy ADPT-SIG and ADPT-VAR. For both adaptive strategies, we used an identical probability database. Figure 11 plots the risky exit rate as well as the average speed as a function of the inflow ratio.

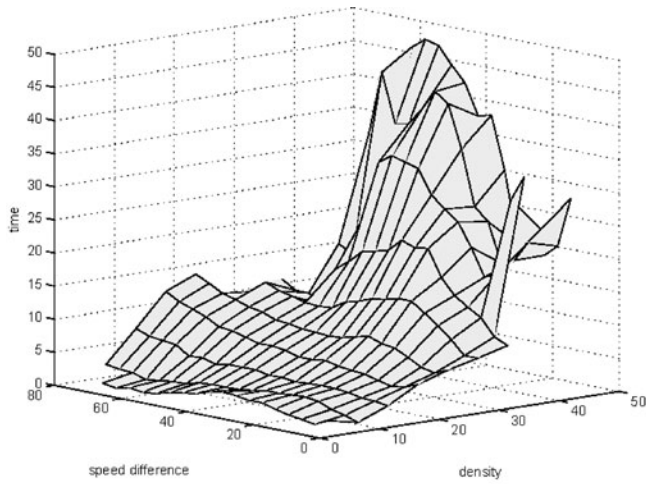
One of the immediate conclusions is that the adaptive strategy “works” in the sense that it maintains a flat risk probability for different traffic densities. For the ADPT-VAR algorithm, this is very close to the target value of 10%. For the ADPT-SIG algorithm, this is slightly higher at around 14–16%, due to the fact that the algorithm uses the same probability database as ADPT-VAR, which had been collected from histograms of VAR-type drivers. However, both values are much higher than the VAR value with a 600-m preparation distance. For the SIG model, the risky exit percentage is highly dependent on the traffic density—we find that the chosen value of 600 m is too small for high traffic densities.

As a note, we see an outlier experiment for VAR at flow ratio 4.5. This happens if, for some reason, there is an unusual number of accidents happening in sensitive locations (e.g., in both lanes at a location where the highway is only two lanes).

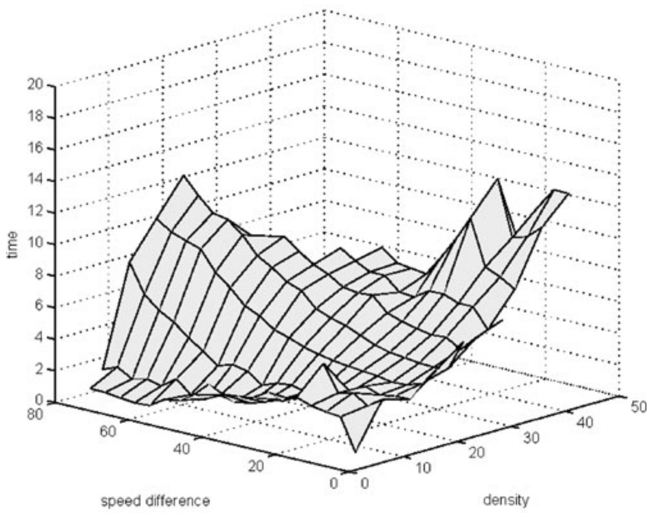
Let us now check the average speed achieved with these strategies, shown in Figure 11b. Contrary to our expectations, there is no clear speed benefit for the adaptive strategy. The SIG agent is clearly faster than ADPT-SIG, while the difference between VAR and ADPT-VAR is minimal (except in a single point that is the artifact of a special traffic event).

There are several reasons for this lack of speed advantage. First, in the American highways modeled in our simulator, there is rarely any speed difference between the highway lanes—the slowdown due to exiting and entering vehicles only affects the rightmost lane. Thus, the aggressive stand of the ADPT strategies to stay on the leftmost lane as long as possible is reflected in very little actual speed gain. On the other hand, by delaying the lane change to the last moment, ADPT vehicles will need to do lane change under much more difficult conditions, which negates the advantage of faster lanes.

Overall, the results show that the choice of driving schools to recommend fixed preparation distances and not to encourage adaptive strategies is a correct one: If adopted by all vehicles, the VAR strategy appears to be the safest and overall fastest choice.

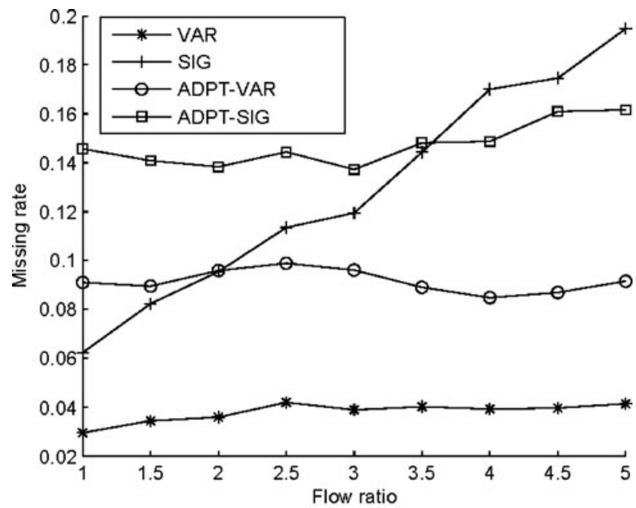


(a) SIG



(b) VAR

Figure 10 Average lane-change time for the SIG and VAR agent in various traffic situations.



(a) Rate of risky exits

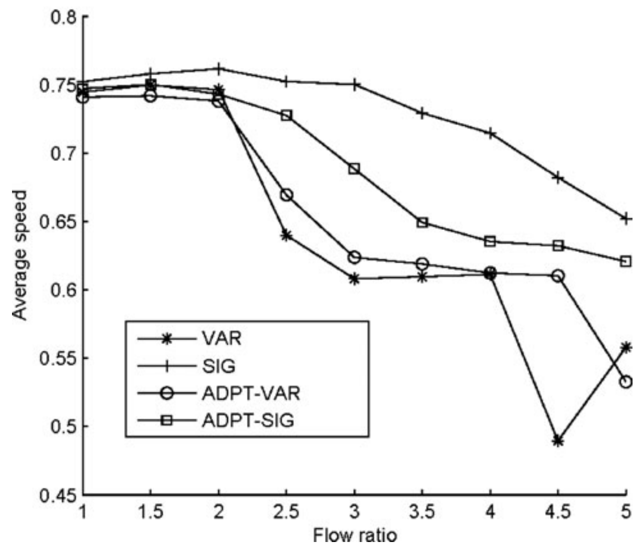


Figure 11 The rate of risky exits and average speed in the function of flow ratio on Highway 408.

Note that in our experiments, all vehicles used the same strategy; it is possible that having a single vehicle performing an adaptive strategy would obtain a more significant speed advantage if the other traffic vehicles perform a nonadaptive strategy.

RELATED WORK

The Terminological Problem: Modeling and Architectural Definition of Agents

In the following we review work related to agent-based systems in traffic simulation. To do this, we need to clarify our use of the term "agent." After the terminological disputes of the 1990s (Franklin & Graesser, 1997), the autonomous agents community had settled on a definition of an agent as an entity that senses its environment and performs actions in the pursuit of its own agenda.

Of course, almost any system can be modeled as an agent-based system, by hypothesizing the existence of an internal agenda that matches the external behavior. This modeling definition is sometimes helpful in analyzing existing systems, but provides no guidance in system building. In this article we prefer the use a more restrictive, architectural definition, where we require that the sensing, agenda, and the process of choosing actions be present explicitly in the system.

Vehicular traffic has the natural aspect of a multi-agent-based system: It represents the interaction between large numbers of vehicles, driven by human agents. Each human agent has her own goals, and proceeds by sensing her own environment, making decisions, taking actions, and interacting, explicitly or implicitly, with other drivers. Thus, any traffic simulation detailed enough to consider individual vehicles will verify the modeling definition of agents. Thus, all the microsimulation models can be perceived as agent models, a view taken, for instance, in Kesting et al. (2008).

Models such as the MOBIL lane changing model (Kesting et al. 2007) and the intelligent driver model (Treiber et al., 2000), which use differential equations to model behavior, can be seen as agents according to the modeling definition but not according to the architectural definition.

Another example includes cellular automata-based models (Nagel & Schreckenberg, 1992), which sometimes are positioned as agent models, for instance, in the NetLogo (Tisue & Wilensky, 2004). Again, we consider these as agents only according to the modeling definition.

In the following, we review some of the contributions to the field of traffic simulation of systems. We follow a recent review paper by (Bazzan & Klügl, 2013) by classifying the agent-based traffic modeling and simulation techniques into (a) agent-based demand simulation, (b) agent-based choice, and (c) agent-based traffic flow simulation.

Agent-Based Demand Simulation

Before we start simulating what happens on the road, we need to first determine how many cars are present, where they entered the road system, and where are they going. These questions are the topic of traffic demand simulation. While early work was modeling directly the distribution of trips, modern approaches to this problem are trying to model the activities performed by humans (such as work, entertainment, shopping, and rest), and then to model the trips that must be taken to perform these activities, possibly also taking into account expert guidance (Seyedabrishami, 2011). Activity-based traffic demand modeling is a natural fit for agent-based systems.

The ADAPTS model (Auld & Mohammadian, 2009) separates the activity generation from the activity planning and scheduling. A similar approach, with emphasis on the uncertainties of decision making, is taken by Sun, Arentze, and Timmermans (2012). The different planning processes of private and commercial vehicles are modeled in Joubert, Fourie, and Axhausen (2010). Another research direction involves the modeling of the cognitive and psychological aspects of the travel planning (Arentze & Timmermans, 2005a, 2005b).

Modeling the full planning process is a significant computational expense. As the daily routines of most travelers are largely repetitive, the approach can be scaled up if a set of fully elaborated daily plans are precomputed, and then iteratively adapted by the agents. This is the approach taken by the MATSim-T module (Balmer et al., 2009).

Finally, the overall focus on social networks in the last 5 years was echoed in agent-based demand simulation by focusing on the role of the social interactions and social networks on travel planning in works such as Ettema, Arentze, and Timmermans (2011), Han, Arentze, Timmermans, Janssens, and Wets (2011), and Hackney and Marchal (2011).

Agent-Based Choice Simulation

Once we determined the goals of the agents participating in the traffic, we need to model the various choices the agents can make with regard to their transportation. The choices might involve the mode of transportation (e.g., the agent might take a train, bus, or a car) as well as the route followed (Lee, Ran, Yang, & Loh, 2010). In the choice of the route, the agent might consider aspects such as length, congestion, tolls, and familiarity with the road. A particularly challenging aspect is represented by the problem of congestion, as this depends on the interaction between the decisions of multiple agents.

One way in which the choice of the agents can be modeled is a game-theoretical approach. In particular, in congestion games, agents that pick the less popular alternative route receive a higher reward. The participating agents might deploy a mix of strategies—for instance, some agents might make decisions ignoring the current congestion, while others might use strategies taking into account the current congestion and the decisions of other agents. One approach to implement agent-based choice simulation is to learn the decision model of humans, for instance, through reinforcement learning as shown in Chmura and Pitz (2007) and Klügl and Bazzan (2004).

The amount and quality of information affect the choices of the agents. Paradoxically, more information might not necessarily lead to better choices, as uncoordinated agents might overcrowd routes that appeared better at the moment of their decision making. The decision making under various information propagation models had been studied by Rossetti et al. (2002), Klügl and Rindsfüser (2011), and Panwei and Dia (2006).

Agent-Based Traffic Flow Simulation

Finally, after the travel decisions and the route to be followed have been modeled, the simulator needs to model the decisions taken by the agent during driving in the traffic. In general, the types of actions taken by the agent depend on the driving environment. In the case of highway driving, the challenges involve the car-following models and the lane-change models. In the case of a single carriageway road, to this we need to add the decisions concerning overtaking. Finally, in urban driving, decisions involve interactions with pedestrians, decision to pass on the amber light, and driving in intersections.

There have been relatively few papers that implement highway simulation with agent-based models. If we extend our definitions to the modeling definition of agents, we can consider here the early work of Burmeister, Doormann, and Matylis (1997), or the cellular automata-based work of Nagel and Schreckenberg (1992). There is a significant amount of work based on continuous car-following models, which sometimes are extended to cover lane changes. These models are sometimes presented as agent-based models (e.g., the models surveyed in Kesting et al., 2008, 2009). As the majority of these models are expressed in form of differential equations, we classify them as virtual physics models.

Some elements of single carriageway road simulation, such as overtaking, are considered in Paruchuri, Pullalarevu, and Karlapalem (2002).

The majority of the agent-based traffic simulation work has been done under the assumption of urban driving. For instance, Ehlert and Rothkrantz (2001) describe the architecture of an agent-based simulator prototype for urban driving. This system matches well the architectural definition of the agent, as the different decisions are explicitly reasoned about.

Doniec, Mandiau, Piechowiak, and Espié (2008) describe a behavioral traffic simulation model and apply it to the problem of realistic simulation of road junctions, presenting it as a multi-agent coordination problem. The system models the traffic rules of priority giving and the psychology (impatience levels) of the driver agents.

Another research project concerns the ARCHISIM simulator (Espié & Auberlet, 2007), which models in a realistic way the perception and reasoning process of human drivers, which includes their model of the behavior of surrounding vehicles. More recent work extends this model to the way human drivers anticipate special situations, such as the movement of emergency vehicles, motorcycles, improperly parked vehicles, and so on (Ksontini, Espié, Guessoum, & Mandiau, 2012).

Benenson, Martens, and Birfir (2008) describe an agent-based model of parking in the city, which includes both physical models of speed and cognitive models of the agent, which involve decision making about high-level factors such as the cost of parking, the distance to home, and the time spent in looking for parking spots.

Fiosins, Fiosina, Müller, and Görmer (2011) explore the challenge of integrating the tactical and strategic behavior of drivers in an urban setting. In this setting, strategic planning involves the planning of the route within a city, while tactical planning is the planning of the speed and the lane within a single route segment, including behavior with regards to the traffic lights. The proposed approaches are stochastic shortest path calculation R-SSPPR with Bayes posterior probabilities for historical information for the strategic part, and distributed multiagent reinforcement learning for the tactical part, where the driver agents learn the optimal cooperative actions.

A special case of traffic flow simulation is the acquisition of driver models from a human subject's behavior in simulated driving environment. Tanaka, Nakajima, Hattori, and Ishida (2009) describe a method through which the driving models of different humans (e.g., old versus young) can be extracted from the driving logs recorded from a human driver in a three-dimensional (3D) driving simulator. The model is described using predicate logic rules. The authors use interviews to elicit the reasoning behind the driver's decisions. To reduce the complexity of the data, the system incorporates certain a priori assumptions about the human driver; for instance, it assumes that the human drivers cannot perform intentional operations at a rate higher than one every 2 s, and filters out faster operations as unintentional. This is similar to the cognitive limitations model we deployed.

Positioning of YAES-DSIM in the Context of Agent-Based Simulation Approaches

The YAES-DSIM simulator, with both the contributions described in this article and previous contributions (Luo & Bölöni, 2010), falls in the category of an agent-based highway simulation. YAES-DSIM agents follow the stricter, architectural definition of an agent. However, for the experiments described in this article, we do not use an agent-based simulation of traffic demand; rather, we rely on real-world demand data measured on a toll highway.

Overall, there are relatively few directly comparable projects, if we are restricting ourselves to highway simulation. There are projects that use the cellular automata definition of agents, such as Nagel and Schreckenberg (1992) and the simulator experiments based on NetLogo. Another large group of highway simulators uses the term *agent* for systems described with differential equations (Kesting et al., 2008). The latter ones we call virtual physics models, and our work can be considered an extension of these types of systems with higher level decision models, modeling conscious decision.

If we extend our sight to a larger set of systems, we can also compare our approach with urban traffic simulators. Direct comparisons are difficult to make, because the simulators of urban traffic consider different scenarios - for instance intersections and stop lights instead of highway lane changes and entrance/exit scenarios. Nevertheless we can compare the overall architecture of the systems. In this category, we can find many systems which meet our architectural definition, such as Ehlert and Rothkrantz (2001), Doniec et al. (2008), Espié and Auberlet (2007), Benenson et al. (2008), and Fiosins et al. (2011). The majority of these systems, however, focus on the high-level decisions on the agent system coupled with simplified models of the low-level vehicle control. This is justified by the fact that in the stop-and-go traffic of a dense urban environment the vehicle physics has a lower importance.

In conclusion, we find that the agent model of our system has close relatives in the general field of agent-based traffic simulation projects—especially if we include simulators for urban traffic. On the other hand, our system is unique in the application of agents (in the architectural definition of the world) for the challenges of highway traffic simulation, as well as in the integration between high-level agent models and virtual-physics type equations.

CONCLUSIONS

This article described a microscopic highway simulator where an agent-based model of the conscious driver is integrated with a virtual physics model of highway driving. In situations when the driver uses highly learned driving skills, such as on highway stretches far away from exits, the model will fall back on the finely tuned virtual physics-type microscopic models. On the other hand, the agent-based component is able to model the tactical and strategic decisions of the agent, such as the tactic of aligning the speed with the destination lane when changing lanes, or the strategy to adaptively plan for a highway exit function of the traffic and speed differences between lanes. As the agent-based component operates through rather than instead of the virtual physics models, the approach ensures that there are no abrupt driving style changes, and the constraints enforced at the lower levels, such as the safety conditions, will still be verified.

We find that this architecture successfully merges the benefits of virtual-physics-based microscopic traffic simulation and agent-based driver models. Our ongoing and future work involves the application of the architecture to a number of new applications, such as the study of the impact of variable speed limits, intelligent cruise control systems, and blind-spot warning systems. We also believe that similar architectural solutions of integrating virtual physics and agent based systems could be beneficial for other simulators, such as those modeling urban traffic.

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