Enhanced Presence in Driving Simulators Using Autonomous Traffic with Virtual Personalities

Abstract

The paper summarizes a project to increase the sense of presence within a driving simulator while interacting with autonomous traffic. The project sought to model natural variations in ambient traffic to emulate identifiable driving styles for different categories of driver. Probability distributions combined with decision histories were employed to characterize speed choice while providing a mechanism for introducing temporal and spatial variation in speed changes. These efforts produced “virtual personalities” representing different categories of ambient traffic including generic, male, female, old, drunk, aggressive, cautious, and fatigued. A user evaluation of the ambient traffic concluded that naturalistic variation in behavior can significantly contribute to the subjective realism of the interaction with traffic simulation.

1 Introduction

High-fidelity driving simulators are increasingly being used for conducting experiments on driver behavior, for evaluating in-vehicle systems, and for traffic engineering. However, for these applications to provide valid data, the virtual driving environment must be realistic enough to generate responses that are representative of those apparent in actual driving conditions. Traditionally, realism as a quality has been evaluated in terms of the physical appearance of objects in a scene. This may include consideration of such attributes as image resolution and fidelity relative to the physical characteristics of the real object. In addition, realism as a quality can also be evaluated in terms of the behavior of the objects within the scene, relative to the behavior of corresponding objects in the real environment.

In driving simulators, for example, while much attention has been paid in simulator development to improving the realism of sensory cues and feedback, relatively less effort has been given to improving the behavioral realism of traffic activity in the simulated environment. Because vehicle interaction is integral to the driving experience, it is important that the simulated traffic appear to behave and interact realistically with the subject driver in the simulation environment.

Typically, driving simulators operate with two classes of vehicle in the environment: event traffic and ambient traffic. Event traffic are vehicles that are hardwired to perform specific actions when certain conditions are realized. These vehicles are used to maintain experimental control with regard to predefined traffic events so that the driver is systematically exposed to repeatable
scenarios relevant to a particular research question. For example, to detect the effect of fatigue on driver attention, event traffic might be scripted to form a stationary line ahead of the subject driver to measure the reaction time of the driver’s braking responses (Ward, 1997). The second main class of simulated vehicles is ambient traffic. This vehicle type does not have prescribed actions. Rather, these vehicles operate autonomously in accordance with general traffic rules to give the impression of a populated traffic environment.

These classes of traffic relate in several ways. Firstly, ambient vehicles may be triggered to evolve into an event vehicle and engage in a specific scenario (and, conversely, after completing an event, a vehicle may be absorbed by the ambient traffic). Secondly, the ambient traffic serves to camouflage the event vehicles and provide a natural flow of benign events dispersed among the predefined scenarios. Note that the vehicles in a scene must be managed so that any interaction of the ambient traffic with the event traffic does not interfere with the emergence of specific scenarios. Thirdly, the ambient traffic provides the driver with the overall experience of interacting with a natural flow of traffic. Thus, the validity of the driver experience in the simulated environment will be improved in relation to the realism of the ambient traffic behavior.

To support a methodology to generate realism of ambient traffic, it is necessary to presuppose some defining attributes of “realistic” traffic. These attributes can be related to the essential nature of human operators of vehicles:

- **Intelligence**: Individual ambient vehicles should possess the capacity to autonomously navigate an environment and comply with traffic rules.
- **Variability**: Individual ambient vehicles should demonstrate some variation over time and be distinctive from other vehicles in this class.
- **Individuality (style)**: It should be possible to attach to individual vehicles patterns of behavior (virtual personalities) that relate to natural and demonstrable driving styles that originate from demographic groups of drivers or general personality traits, or that are related to known sources of driver impairment.

This paper will outline a proposed model to generate autonomous ambient traffic to represent coherent patterns of behavior associated with the presumed personality of specified driver demographics. Whereas the model can be applied to various driving performance variables (Wright, 2000; Wright, Fernando, Ward, & Cohn, 1998; Wright, Cohn, & Ward, 2000), including gap acceptance (e.g., space separating vehicles in traffic into which another vehicle may merge), lane changing, and following headway (i.e., time or distance between a vehicle and another vehicle ahead of it in traffic), this presentation will focus on the efforts to model speed choice.

## 2 Modeling Autonomous Traffic

The architecture to support the modeling of naturalistic behaviors for autonomous ambient traffic uses a hierarchical control structure for the driving task (Wright et al., 1998). This structure is based on the cognitive model proposed by Michon (1985), which differentiates between the operational, tactical, and strategic processes involved in driving. At the operational level, the driver engages the vehicle actuators to maintain stable vehicle control. These actions support the objectives at the tactical level whereby the vehicle is maneuvered to safely interact with other traffic and follow a path. The overall planning for a trip is undertaken at the strategic level whereby the decisions about the travel mode, timing, and route choice for the destination (goal) are formalized.

A comprehensive model of driver behavior should be structured to take account of all of these driving task process levels and preserve the information flow that represents the hierarchical structure. For the purpose of this paper, the description of the model will focus on the driver behavior model for supporting the tactical level of the driving task. The strategic level can be omitted because the route of each autonomous vehicle through the environment is chosen randomly at run-
time. The operational level supports the tactical level objectives in terms of steering, braking, and acceleration, based on proportional control models derived from Newton’s equations of motion. For example, the steering control method is based on the Tangent Point oriented Curve Negotiation (TCPN) model described by Boer (1996), but applied to an ideal path defined along the center of each lane.

2.1 Driver Behavior Model

The driver behavior model (DBM) described here is responsible for tactical-level speed choices in response to prevailing circumstances in the simulated environment. The model has a number of stages to generate each successive speed choice, as illustrated in figure 1. Firstly, the model assumes an approximate probability distribution of speed choice (stage 1). In stage 2, this is then configured in relation to contextual factors (speed limit, current maneuver, and so on), and also characteristics of the specified virtual personality, if any (stage 3). The distribution now represents the inter-driver behavioral variability for an explicit category of drivers (such as fatigued, drunk, old) in the current circumstances.

In the final stage (stage 4), a random behavioral choice (in this case speed, but also headway or critical gap acceptance) is sampled from the inter-driver distribution. In this way, the model injects natural randomness and unpredictability into the simulation while still reflecting the behavioral data underlying the distribution curve (indicative of the assigned personality). In addition, past choices that were made in similar contexts are included in the process to manifest some stability and consistency of driving style. This concept is explained in more detail later.

2.1.1 Stage 1—Identify Surrogate Distribution for Observed Behavior. In specifying a model to represent realistic speed choice, it is not practical to observe actual speeds in all possible conditions and reproduce these same values under identical simulated conditions. Instead, it is necessary to generate a model based on a surrogate distribution that reasonably approximates the expected distribution of observed data. This involves choosing an appropriate distribution type (such as normal, log normal) with the assumption of appropriate distribution parameters (mean, standard deviation) suggested by the data obtained from a review of the relevant literature.

In terms of speed behavior, the normal probability
distribution curve approximates the distribution of speed choices over a population of drivers (Blana, 1997). The probability of a driver exhibiting a speed, \( x \), is described by equation (1), where \( \mu \) represents mean speed and \( \sigma \) represents the standard deviation (meters/second):

\[
\text{Probability } y = \frac{1}{\sigma \sqrt{2\pi}} e^{-(x-\mu)^2/2\sigma^2}
\]  

(1)

Bennet (1994) observed a relationship between mean speed and standard deviation approximated by equation (2). Although such a relationship may not be universal in all contexts, this does provides a simple first approximation for characterizing speed variability.

\[
\sigma = 0.481 + 0.12\mu
\]  

(2)

### 2.1.2 Stage 2—Model Contextual Factors.

Based on the assumed surrogate distribution, it is necessary to specify the parameter values for this distribution in terms of dependent contextual factors. This specification will permit the generation of speed choices that are realistic in terms of similar contextual factors within the simulated environment. The most significant and intuitively separable contexts with respect to speed choice are speed limit, road curvature, and distance to junction.¹

**Speed limits.** Kwon-Young (1998) recorded mean speeds in zones marked with 30, 40, and 60 mph speed limits on low-volume roads in which free speed choice, not limited by other traffic, is more likely to be attained. (See table 1.) In table 1, mean speed values have also been inferred linearly for 20, 50, and 70 mph zones. However, the speeds recorded in the higher speed limit zones are deemed to be unrealistically low for representing free speeds. To accommodate more-realistic free speed choice in these zones, mean speeds are estimated assuming a fixed percentage (28%) of vehicles exceeding any given posted speed limit as noted by Kwon-Young for 30 mph roadway limits.

**Road curvature.** Watts and Quimby (1980) investigated aspects of road layout that affect speed choice. This included a comparison of a number of mathematical models that approximate the results of various studies of curve-speed behavior. For the DBM, it is assumed that the primary determinant of speed choice for negotiating a curve is the radius of road curvature (\( R \)). On this basis, equation (3) and (4) are derived by Emmerson (1970) and converted to meters/second (m/sec.) units, representing speed choice on large and small radius curves, respectively.² Whereas the definition of high and low are not made explicit by Emmerson, in this implementation curves with radii <50 m are considered small and those >50 m are considered large, based on the point of intersection of the two equations.

1. Speed choice is also influenced by a number of factors that may not be directly specified or controlled (such as motivational factors, weather, law enforcement, vehicle performance, and locale). Similarly, many of these studies observe the speed that can be accommodated in the prevailing traffic context rather than the desired speed of the driver if conditions permitted free speed choice. Thus, most studies reported in relation to speed limits consider changes in mean speed for the overall traffic rather than for individual drivers. For these reasons, some general assumptions need to be made about models of speed choice for individual drivers representing demographic groups.

2. The limitations of these equations should be noted. Mathematically, equation (4) increases without bound with radius. Eventually road curvature should become insignificant to speed choice. So this is not a good description for large curves. Meanwhile, equation (3) reduces too rapidly towards zero with \( R \), and was found, visually, to be not a very good generator of speed choice for very small curves.

### Table 1. Mean (Free) Speed as a Function of Speed Limit (Based on Kwon-Young, 1998)

<table>
<thead>
<tr>
<th>Speed Limit (mph)</th>
<th>Observed Mean Speeds (mph)</th>
<th>Model Mean Speeds (mph)</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>22.80</td>
<td>22.80</td>
</tr>
<tr>
<td>30</td>
<td>27.90</td>
<td>27.90</td>
</tr>
<tr>
<td>40</td>
<td>33.00</td>
<td>35.60</td>
</tr>
<tr>
<td>50</td>
<td>40.35</td>
<td>45.28</td>
</tr>
<tr>
<td>60</td>
<td>47.70</td>
<td>54.60</td>
</tr>
<tr>
<td>70</td>
<td>55.05</td>
<td>63.68</td>
</tr>
</tbody>
</table>
Table 2. Generic Speed Profile as a Function of Distance to Junction (Van der Horst, 1990)

<table>
<thead>
<tr>
<th>Distance to Junction (m)</th>
<th>Mean Approach Speed (m/sec.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>5</td>
<td>4.83</td>
</tr>
<tr>
<td>15</td>
<td>7.84</td>
</tr>
<tr>
<td>25</td>
<td>9.70</td>
</tr>
<tr>
<td>35</td>
<td>10.80</td>
</tr>
<tr>
<td>45</td>
<td>11.20</td>
</tr>
</tbody>
</table>

Large radius: \( \mu = 20.56(1 - e^{-0.017R}) \)  \( (3) \)

Small radius: \( \mu = 0.894\sqrt{R}/0.3084 \)  \( (4) \)

Junction distance. When approaching a junction, it may be necessary to slow down to yield to other traffic or comply with traffic signal devices. This becomes increasingly critical as the driver gets closer to the junction and has less time (and distance) in which to respond. The resulting speed profile is affected by a large number of issues relating to junction layout, type of junction traversal, and the traffic flow in the intersecting lanes. It is overly ambitious to attempt to account for every possible case. Thus, the DBM adopts a generic model of junction approach behavior related to approach distance, based on an average of the results reported by Van der Horst (1990) for different maneuvers at a conventional T-junction layout. (See table 2.) This data is applied to intersections at which the driver must slow to yield to crossing traffic. In this case, it is assumed that the appropriate speed for negotiating the junction is largely independent of the speed limit. This assumption is extended to the preceding junction approach profile by using a time-based threshold to trigger the slowing behavior.

2.1.3 Stage 3—Model Virtual Personality.
This model also configures parameters to represent identifiable driver characteristics and styles of driving as shown in table 3. These values are extrapolated from data reported in selected published research that includes these driver categories in relevant observational or experimental studies (Wright, 2000).

Gender. The inclusion of gender as a demographic for driving style is based on the general trend for different crash risk and risk-taking behavior for men and women (Evans, 1991). In terms of speed choice, Hagen (1975) investigated gender differences in speed control behavior. From this, an approximation is derived that male drivers adopted faster mean speeds by a ratio of 1.155.

Age. Wasielewski (1982) recorded speeds adopted by drivers between twenty and seventy years of age. Mean speed decreases over this age range by about 1.75 m/sec. These results were observed for drivers traveling at 21.4 m/sec. Speed choice may be more conservative in older age, perhaps in part to compensate for recognized deterioration in perceptual and cognitive functions. To represent these observations, the model assumes a linear relationship, then relates speed reduction to the mean speed driven (so speed reduction with age becomes less significant at lower speeds).

Aggression. Parry (1968) investigated how aggression varies among the driver population. Male drivers are typically more aggressive than are female drivers,
but, with increasing age, male drivers tend to become less aggressive and female drivers become more aggressive. Also, increased aggression is commonly observed in drunk drivers. From this interpretation, aggression may be considered as a symptom of the driving style rather than as an isolated trait. Howe (1997) characterizes aggression in terms of a safety factor, with the aggressive driver presumed to possess a lower safety factor than a more cautious driver. This would suggest that aggressive drivers are located in the risk-taking extremes of the surrogate distribution. Therefore, aggression can be characterized by shifting the mean by a number of standard deviation units into the more extreme percentile range (85th). Similarly, cautious drivers can be equally characterized by shifting the mean into the lower percentile range (15th).

**Intoxication (alcohol).** The legal alcohol limit for driving in the United Kingdom is a blood alcohol concentration (BAC) of 0.8 mg/ml. Kloeden, McClean, Moore, and Ponte (1997) illustrated a 0.794 m/sec. increase in mean speed for a BAC of 0.5 mg/ml. Applying a linear relationship to these results gives an increase in mean speed of 1.58 BAC.

**Fatigue.** In terms of speed behavior, fatigued drivers tend to temporarily increase their speed to increase their feelings of arousal, then let their speed drop again. This is manifested as a significant increase in standard deviation of speed during cases of severe sedation. Tests with prescription drugs at the Center for Environmental and Traffic Psychology (COV) have recorded a 5% increase in speed variability (Brookhuis, 1998).

### 2.1.4 Stage 4—Modify Choice for Natural Representation.

Once a surrogate distribution has been identified and then prescribed by the assumed parameter values for the context and virtual personality, the model can be processed to generate a choice value. However, random choice sampling alone may not be constrained enough to produce a stable behavior that is indicative of that personality definition over time. That is, it is possible that a random process could generate disparate choices on successive samples, resulting in extreme and unnatural changes in speed over short periods. To address these issues, each random choice is combined with the previous choice made in similar circumstances. These past choices are stored in a personal decision history for each ambient vehicle. This combination prevents such erratic jumps between consecutive choices and constrains intra-driver variation to more consistent levels.

As part of the combination, the model also includes consideration of the driver’s propensity to take risks, which biases the choice in either a cautious or risky direction within the distribution. Based loosely upon the idea that drivers modify their behavior to keep subjective risk at some preferred level (Wilde, 1982), the DBM randomly assigns each ambient vehicle a personal risk-taking index to define the relative position of its individual driving style within the probability distributions. This risk-taking index is used to center a triangular fuzzy logic function (named the *intra-driver fuzzy set* in figure 1).

Random choices are combined with past choices by calculating their average, weighted by their corresponding mapping in the intra-driver fuzzy set. That is, the risk-taking index is not part of the average calculation; rather, it is used to configure the averaging function. This process constrains the variability of the random choices to be consistent with the assigned risk-taking style across all modeled behaviors. For example, a higher risk-taking index would correspond to higher speed choices, lower time-headway choices, and the acceptance of smaller gaps.

To avoid maintaining the same behavioral choice for unrealistic lengths of time and to promote intra-driver variation, the model also distributes decision-making over time. However, there have been extremely few (if any) studies of the average choice frequency for driver speed. This is because it is difficult to measure exactly when a driver decides upon a new speed because these processes may be unconscious over time.

Studies of speed behavior often include measures of

3. The decision history looks backward only one decision in time. Deeper histories were also considered, but resulted in too much computational overhead and constraint on intra-vehicle variation.
speed adjustment frequency based on the number of times the driver uses the accelerator/brake pedals. Hagen (1975) compared the frequency of accelerator adjustments between male and female drivers and observed that men used the accelerator more often by a ratio of 1.44. Extending this relationship to actual speed choices, if the generic driver has an arbitrary interval of 10 sec., then the intervals for male and female drivers are estimated as 11.81 sec. and 8.19 sec., respectively.

3 Model Evaluation

Two forms of evaluation were made of the model as applied to the University of Leeds Advanced Driving Simulator (http://mistral.ac.uk). These include a functional analysis of the model’s performance and a user evaluation of the perception of the ambient traffic interacting in the driving simulator. Note that only the model for speed choice has been described here, but the evaluation was based on the full model that included gap acceptance, lane changing, and headway control.

3.1 Functional Analysis

The aim of the functional assessment was to evaluate the performance of the model with respect to the fundamental requirements for simulating realistic ambient traffic, namely intelligence, variability, and individuality (style).

3.1.1 Intelligence. The first of the requirements is that the ambient traffic should possess the capacity to autonomously navigate the road network. This requirement is achieved by the rule-based component of the DBM.

3.1.2 Variability. The second requirement is that the simulated traffic environment should mimic the natural unpredictability of real traffic. Unpredictability is successfully introduced into the simulation through the generation of random choices from probability distributions. Combination with a decision history successfully constrains intra-driver variation to a relatively consistent and unique driving style. However, problems arose in the evolution of the vehicles’ decision histories. Because the history was continually updated to store only the most recent relevant choices, successive iterations of the DBM caused behavior to drift towards the mean. As a result, differences in driving style between vehicles would eventually be lost. This is solved by initializing the decision history based on the personal risk-taking index, but not updating the history as subsequent choices are made. Significantly, this change undermines the whole need to store a decision history.

3.1.3 Individuality (style). The third requirement is the ability to specify various individual virtual personalities that are distinguishable through the unique characteristics of behaviors manifested within the simulated traffic environment. For this evaluation, examples of driving style from each virtual personality type were analyzed using a $k$-means clustering algorithm. The $k$-means algorithm works as follows:

1. An initial population consists of a set of examples and a number of cluster centers (or exemplars).
2. For each exemplar, find the $k$ nearest neighbors amongst the examples.
3. Move each exemplar to the center of its neighbors.
4. Repeat step 2 and 3 until the exemplars stabilize.
5. Clusters of examples are then defined by their corresponding nearest exemplars.

For this evaluation, driving style examples were defined by 22-dimensional vectors corresponding to the contents of the vehicles’ decision histories. An initial population was created from ten examples of each personality type: generic, male, female, aggressive, cautious, old, drunk, and fatigued. A corresponding exemplar vector was also defined based on the mean behavior of each personality type. A value of $k = 10$ was chosen, reflecting the ideal number of examples in each cluster.

The objective of this analysis was to evaluate the distinctiveness of the different virtual personalities based on their tendency to cluster together. In this regard, it was apparent that only the examples of fatigued drivers clustered together completely accurately. This can be explained by the unique traits of its behavior. Whereas
the other driver types are consistent in their level of risk-taking behavior, the fatigued driving style is comparatively erratic.

There also appeared to be a strong correlation between the aggressive characteristic and the other driver categories. In other words, the categories that can be presumed to share more-aggressive personalities (male, aggressive, drunk) also tended to cluster together. Similarly, the more-cautious personalities (female, cautious, old) tended to group together. (This observation was reinforced by a $k = 3$ test involving clusters for generic, aggressive, and cautious drivers only.) These results suggest that aggression and caution are key traits that discriminate between the behaviors of the different driver categories.

On this basis, it appears that the model does satisfy the main functional requirements to reproduce individual personalities for ambient traffic, at least in terms of representing fatigued, aggressive, and cautious driving styles. However, it must also be determined if the manifest behaviors are perceived by persons interacting with the ambient traffic to be realistic and indicative of recognizable personalities.

### 3.2 User Evaluation

The user evaluation comprised three separate studies to examine the perceptions of persons interacting with the ambient traffic. Two studies had subjects observe traffic operating within a simulated environment and attempt to identify the driver category represented and judge the apparent realism of the manifest behaviors. In these studies, subjects were passive observers and did not interact directly with the traffic. A third study had subjects interact with the vehicles in the driving simulator to again judge the perceived dynamic realism of the ambient traffic behaviors.

The first study involved six subjects who observed single examples of ambient vehicles representing male, female, old, fatigued, drunk, and cautious drivers within the context of generic ambient traffic. Each vehicle corresponding to a particular driver type was of a different color to distinguish them from each other and the generic traffic. Subjects passively witnessed the behavior of these vehicles from different elevated viewing positions in a simulated road network. This allowed subjects to observe the behaviors of groups of vehicles along the road network, including a screen speedometer to monitor speed choice. Subjects were free to select vehicles and observation views at their own discretion to formulate an opinion about the nature of each ambient vehicle. Subjects were then required to assign descriptors to each vehicle color representing a driver category.

To allow the subjects some freedom, this list of descriptors included not only the manifest driver categories (aggressive, old, drunk, cautious), but also some general driving style traits (erratic, risky, swerving) and some other general control terms (normal, young).

The pattern of descriptor assignment suggested several response tendencies. First, subjects were better able to identify driving style attributes than the actual driver category. For example, the vehicles representing drunk drivers were consistently associated with aggressive and risk-taking attributes (including the recognition of reduced steering performance). Whereas these are appropriate associations of the driving style, none of the subjects correctly identified this as constituting drunk drivers. Similarly, the driving style of the fatigued driver traffic was consistently described as erratic, but was never identified specifically as a fatigued driver. This suggests that people may—at least initially—form perceptions of other traffic based on the style of driving rather than the presumed type of driver.

Second, as suggested in the preceding functional analysis, the primary dimension by which people perceive the driving style of traffic appears to be aggression—caution. In this case, the aggressive and cautious ambient vehicles both resulted in the highest levels of correct classifications (66.7% and 83.3%, respectively). Similarly, when given paired examples of only aggressive and cautious traffic, all subjects were able to identify the aggressive examples by virtue of faster speeds and acceleration, more overtaking, and sharper braking.

In the second study used, ten subjects observed mul-

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4. Note that random choice generation was disabled here to maintain integrity of the virtual personalities.
tiple examples of vehicles that defined types of traffic that differed in the degree of autonomy and variability:

- **Traffic 0—Dumb traffic**: Speed choice is fixed to the 60 mph speed limit.
- **Traffic 1—Intelligent nonrandom traffic**: The speed choice DBM is operational, but with no random choice generation.
- **Traffic 2—Intelligent random inconsistent traffic**: The speed choice DBM and random choice generation is operational, but the decision history element is disabled so that there is no constraint on individual variability.
- **Traffic 3—Intelligent random consistent traffic**: The full speed choice DBM, random choice generation, and decision history are all operational, constraining variation into consistent driving patterns.

Subjects were required to rate each traffic type in terms of the variability among vehicles in the traffic (unpredictability), the variability within individual vehicles over time (erraticness), as well as the overall realism of the traffic behavior. Ratings were made on a seven-point scale with larger values indicating more of the quality rated. The mean ratings of realism were 1.6, 4.1, 5.6, and 5.7 for each traffic type, respectively. These data were analyzed using contrasts (ANOVA) to represent specific comparisons between traffic attributes: namely, dumb (Traffic 0) versus intelligent traffic (Traffic 1, 2, and 3 as a group); nonrandom (Traffic 1) versus random traffic (Traffic 2 and 3 as a group); and inconsistent (Traffic 2) versus consistent (Traffic 3). This analysis suggests that the dumb traffic was rated as significantly less realistic than all other intelligent traffic types \( F(1, 9) = 100.72, p < .0001 \). The nonrandom traffic was rated significantly less realistic than both intelligent traffic types incorporating random choice in the DBM \( F(1, 9) = 15.20, p < .005 \). There was no significant difference between the random-consistent and random-inconsistent traffic types \( F(1, 9) = 0.07, \text{ns} \). This suggests that random variation between vehicles is more important to perceived realism than is the consistency of an individual's behavior over time.

Across these traffic types, ratings of unpredictability and erraticness were significantly correlated \( r = 0.69, p < .00001 \) suggesting that inter- and intra-vehicle variation is perceived by observers to be related. Both sources of variation were also significantly related to perceived realism of the observed traffic behavior. However, the form of this relationship indicated different trends. As shown in figure 2(a), the unpredictability of traffic defined in terms of variation among vehicles had a statistically significant linear relationship with perceived realism \( F(1, 28) = 4.90, p < .05 \) accounting for 15% of the shared variation in ratings. This suggests that, as the variability between vehicles increases, so does the
perceived realism of traffic. In contrast, the variability of behavior for individual vehicles over time had a statistically significant quadratic relationship with perceived realism as shown in figure 2(b) \( F(2, 27) = 5.24, p < .01 \). This instead suggests that, beyond some point, further variation in the behaviors of a particular vehicle over time is not perceived to be natural.

In the third study, six subjects interacted in the driving simulator incorporating intelligent ambient traffic based on the types used in the second study described previously. The ambient vehicles responded to the subject vehicle as any other entity in the road environment based on rules governing their behavior (although they were more “cautious” at junctions, given that it was not possible for the simulated vehicles to know in advance the direction the subject driver would eventually take).

Subjects drove the simulator on two occasions for 15 min. each. On one occasion they interacted with a version of Traffic 1 (intelligent nonrandom traffic), and on the other occasion they interacted with Traffic 3 (intelligent random consistent traffic). All subjects reported that the interactive driving experience with the random but consistent traffic (Traffic 3) was the most realistic. This again suggests the importance of variability between vehicles in traffic in terms of perceived realism.

4 Discussion

The effectiveness of driving simulation applications is closely related to the realism of the virtual environment, including the behavior manifested by the simulated traffic. This paper has presented a driver behavior model (DBM) that attempts to satisfy three requirements for simulating realistic ambient traffic. Whereas the actual implementation included the modeling of additional driving behaviors including gap acceptance, lane changing, and headway control, the detailed description within this paper applied only to speed choice.

4.1 Intelligence

The first requirement states that traffic should possess the capacity to autonomously navigate an environment and manifest behavior consistent with the conditions of the road network. The DBM provides autonomous control by using a rule-based framework to negotiate the simulated road environment. This provides a method for ambient traffic to respond automatically and naturally to environmental conditions such as curves and intersections as well as traffic control devices. The user evaluation suggested that the apparent intelligence is a significant determinant of the perceived realism of the traffic.

4.2 Variability

The second requirement is that traffic should manifest natural variation in behavior both in terms of distinguishing groups of vehicles and changes in behavior over time. This is achieved in the DBM using probability distributions and random sampling algorithms, combined with a personal decision history to constrain behavioral variation to relatively stable and unique driving styles. The user evaluation suggested that the variation that distinguishes among vehicles is perhaps more important (salient) for perceived realism than is the variation within individual vehicles over time. Indeed, too much “erraticness” may be perceived as unrealistic, reinforcing the need to constrain random variation.

4.3 Individuality (Style)

A third requirement is the ability to manifest behavioral attributes indicative of distinguishable driving styles or virtual personalities. It was apparent from the functional analysis and user evaluation that the dimension of aggression—caution is a primary attribute by which the driving style of traffic is perceived. Unless these attributes are typical of a particular category (such as male, old drivers), the driver type may not be correctly identified.

Overall, the model and evaluation suggest that ambient traffic that can autonomously navigate a road network and display natural behavioral variation can add to the realism of the simulation experience. However, the use of ambient traffic should be carefully managed such that the experimental control of a study is not jeopar-
dized. First, the amount and type of ambient traffic should be selected so that the random variation of traffic behavior does not produce radically different driving environments between subjects and experimental conditions. Second, the interaction between ambient and event traffic should be defined such that control of the specified scenario is maintained. These requirements imply the need for the capability to manage the interaction and evolution between ambient and event traffic in simulated environments so that the advantages of ambient realism and event control can be balanced.

5 Conclusion

During the functional analysis of the DBM’s choice generation process, some limitations were highlighted. Firstly, to prevent convergence to mean behavior, past choices are no longer updated over time, which renders the decision history structure largely redundant. Secondly, this model does not permit explicit control over the level of behavioral variation within an individual’s driving style. Thus, the model has limited applicability for the replication of explicit driving data, or the generation of specific patterns of variation (such as greater speed variation as a function of increased fatigue). This problem arises because randomness is introduced prematurely into the decision-making process, necessitating the use of the fuzzy combination mechanism to constrain variation (figure 1).

The limitations in this area have been solved by extending the use of probability distributions to the intra-driver level, as shown in figure 3. As in the original model, a surrogate distribution is assumed for the current behavior (speed, headway, gap acceptance), then the parameters of the curve (mean, standard deviation) are configured to reflect characteristics of the vehicle’s context and virtual personality.

The personal risk-taking index of each vehicle defines the relative position of its individual driving style within the inter-driver distributions. This provides the mean (center) of a second normal intra-driver style distribu-
tion. The standard deviation of this distribution reflects precisely the desired magnitude of an individual’s behavioral variability over time.

In this model, random choices are sampled from the new intra-driver distribution. In so doing, the DBM generates variability to specification rather than having to approximate it through fuzzy combination (figure 1). This new design shifts the emphasis towards a “bottom-up” emulation of traffic unpredictability. In other words, the variability of traffic behavior emerges from the driving styles of individual vehicles, rather than the other way around.

This modification to the DBM greatly simplifies the choice generation process. It removes the need to maintain a decision history for each ambient vehicle and significantly improves the accuracy of the variability emulation. For these reasons, the model illustrated in figure 3 becomes the final recommendation for the DBM.

Because most of the data reported in this study is based on passive observation of traffic, there is a need for future research to provide validation data based on interaction with the ambient traffic. In addition to reports of perceived realism, such data should include analysis of the respondent’s own driving behavior in response to interactions with ambient vehicles. Moreover, there is ample scope for enhancements and additions to this proposed DBM, particularly in the area of computational performance. There are also possible new directions such as more psychological behavior modeling, macroscopic traffic management, and the development of a dynamic scenario control architecture. With proper consideration of these issues, similar models could be expanded into an extremely powerful and flexible traffic generation tool.

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