A Personality Model for Animating Heterogeneous Traffic Behaviors

Abstract

How to automatically generate realistic and heterogeneous traffic behaviors has been a much needed yet challenging problem for numerous traffic simulation and urban planning applications. In this paper, we propose a novel approach to model heterogeneous traffic behaviors by adapting a well established personality trait model (i.e. Eysenck's PEN model) into widely-used traffic simulation approaches. First, we collected a large amount of user feedback while users watch a variety of computer-generated traffic simulation video clips. Then, we trained regression models to bridge low-level traffic simulation parameters and high-level perceived traffic behaviors (i.e. adjectives according to the PEN model and the three PEN traits). We also conducted an additional user study to validate the effectiveness and usefulness of our approach, in particular, high correlation coefficients and the pearson values between users' feedback and our model predictions prove the effectiveness of our approach. Furthermore, our approach can also produce interesting emergent traffic patterns including "faster-is-slower effect" and "sticking-in-a-pin-wherever-there-is-room effect".

Keywords: heterogeneous traffic, behavioral animation, personality traits

1 Introduction

Traffic simulation plays a useful role in studying traffic problems. The usefulness of traffic simulation becomes more obvious when a traffic system is too complex to describe using abstract mathematical models. For example, traffic simulation can dynamically reproduce realistic traffic flows, traffic accidents and other traffic phenomena in a low-cost and efficient manner. It can also reproduce the spatio-temporal variations of traffic flows, and is of great help in quantitatively analyzing vehicles, drivers, pedestrians, roads and traffic characteristics. Traffic simulation can visually present the dynamic conditions of vehicular flows in the road network, for example, whether there is congestion at specific locations, whether there are traffic accidents and what measures should be taken when facing such problems. As a result, traffic simulation is an efficient and flexible tool in assisting and optimizing traffic plan, design, regulation and even urban development. In addition, traffic simulation has been increasingly used in entertainment applications, such as racing games, virtual tourism, driving training, special effects in movies and games, and so forth, thus leading to an increasing need to incorporate realistic and immersive traffic scenarios into various virtual worlds.

A significant portion of existing traffic simulation effort has been focused on physics-based traffic models; only limited works have been centered on incorporating human factors into existing traffic models [1–3]. However, in real-world scenarios, human factors play a critical part to form distinct driving patterns and different drivers typically have their own driving styles (i.e. driving behaviors), thus giving rise to heterogeneous traffic flows. In practice, traffic simulation in graphics has reached a point where heterogeneous and lifelike traffic behavioral animation is warranted, as the ultimate target is to simulate traffic as realistic as possible and facilitate other visual applications. Therefore, it is important for traffic simulation systems to produce realistic and heterogeneous traffic flows in virtual worlds. To this end, in this paper we choose personality traits as the main factor to govern drivers' overall driving behaviors although we admit that many other human factors also come to play, because personality traits are relatively easy to identify and trait theories have been well established. We focus on generating heterogeneous traffic behaviors by creating differences in drivers' underlying personalities.

Recently, several research efforts have been conducted to incorporate human personality traits into the simulation of autonomous agents [4, 5]. Surprisingly, to the best of our knowledge, no similar effort has been attempted to incorporate personality traits to traffic simulation application to date. Following the lead of [4, 5], in this paper we aim to generate heterogeneous and realistic driving behaviors by incorporating the PEN model into the simulation of traffic flows. Specifically, we emulate drivers' personality traits by tuning these low-level simulation parameters of a modern physics-based traffic model [6] and explore the resulting effects of personality traits on the overall traffic simulation. Conventionally, users need to first understand a traffic model and then set the low-level simulation parameters in a trial-and-error manner to achieve the desired diversity of traffic flows. This method is time-consuming, inaccurate and inefficient.

In this work, we automatically map low-level traffic simulation parameters to established high-level behavior descriptors including the three factors of the PEN model and six adjective descriptors, by training an optimal regression model. The used training dataset is collected via a finely designed user study. With our approach, users can be relieved from tedious and time-consuming effort of manually tuning low-level traffic simulation parameters. To demonstrate the usefulness of our method, we further apply our method to various urban traffic scenes. We also conducted an additional user study, and high correlation coefficients and their significance between users' feedback and our model predictions prove the effectiveness of our approach. Besides generating realistic heterogeneous traffic flows, emergent traffic patterns including the *faster-is-slower effect* and the *sticking-in-a-pin-wherever-there-is-room effect* can be well observed in the simulation results by our approach.

2 Related Work

2.1 Traffic Simulation

Traffic modeling approaches can be roughly divided into three categories, namely, microscopic methods, macroscopic methods and mesoscopic methods, respectively. Interested readers are referred to the latest traffic simulation survey [7].

The most popular traffic simulation methods are microscopic traffic models, in which the fundamental assumption is that the acceleration of an individual vehicle is determined by the neighboring vehicles in the same driveway, especially the closest vehicle. In 1950, Reuschel [8] introduced early microscopic traffic models. Gerlough [9] described some form of car-following set of rules. Newell [10] explored the non-linear effects in the dynamics of car following. Nagel and Schreckenberg [11] simulated traffic by means of cellular automata and the resulting Nagel-Schreckenberg model has been extended widely. Recently, the intelligent driver model (IDM) [12] has been proposed by Treiber et al., and enhanced by Kesting et al. [6].

In the direction of macroscopic traffic models [13], Lighthill and Whitham [14] and Richards [15] independently proposed the same traffic model as the oldest macroscopic traffic model. This fluid-dynamic model was also termed the LWR model, in which the key assumption is no vehicles are entering or leaving the freeway and the traffic velocity relies merely on traffic density. To improve this model, Payne [16] and Whitham [17] developed a traffic model with two variables thus leading to the PW model. The PW model has been proven to have negative velocities under some conditions. Zhang [18] made some improvements to the PW model by removing incorrect behaviors. In addition, researchers also proposed mesoscopic gas kinetic approaches. Prigogine and Andrews [19] first proposed a Boltzmann-like model for traffic dynamics. Later improvements were made by Nelson and his colleagues [20] and some other researchers.

Recently, there are a number of interesting developments in traffic simulations. For example, Sewall et al. proposed a hybrid technique to simulate both discrete vehicles and aggregated behavior by coupling continuum and agent-based traffic models [21]. Lu et al. [22] presented an accident-avoidance full velocity difference model to animate traffic flows in rural scenes. Wilkie et al. [23] introduced a fast technique to reconstruct traffic flows from in-road sensor measurements or procedurally generated data for interactive 3D graphics applications.

2.2 Modeling Driving Behaviors with Human Factors

To date, most of existing traffic simulation works model driving characteristics and behaviors without taking human factors into consideration. A few traffic models have been proposed to handle human factors [1–3]. However, none of them is aimed to simulate driving behaviors with human factor aspects for computer animation applications. The main difference between our work and the above human factor-incorporated traffic models is, they typically model human factors within existing physics-based frameworks; instead, our work incorporates an independent personality model to a mainstream traffic simulation model in order to tailor the resulting driving behaviors.

2.3 Personality Trait Models

Psychologists develop trait theories to study human personalities. The big three-factor model [24] was proposed in 1985, which claimed that personality can be reducible to three major traits that categorize personality as Psychoticism, Extraversion and Neuroticism. Therefore this three-factor model is also dubbed as the PEN model. The Psychoticism trait is a personality pattern typified by aggression and egocentricity. The Extraversion factor is a personality characterized by projecting one's personality outward and it is typically associated with high levels on positive behaviors (e.g. active, responsible and sociable). The last factor, the Neuroticism, describes an individual's tendency to become upset or emotional and it is characterized by high levels of negative affect such as anger, tension, and so on.

Another widely-known personality model is the big five-factor model, which was developed by Costa and Mccrae [25]. The five factors are openness, conscientiousness, extraversion, agreeableness and neuroticism; therefore, the five-factor model is also called OCEAN, NEOAC, or CANOE. Both the PEN model and the CANOE model treat extraversion and neuroticism as central dimensions of human personalities. Although these two well-known personality trait models are depictive, only the PEN model offers a detailed explicit causal explanation: it suggests that different personality traits are caused by the properties of the brain, as the result of genetic factors [24]. In contrast, the CANOE model just presumes that there is a role of genetics and environment but offers no clear explanation of causality. More importantly, the CANOE model has been criticized for losing the full orthogonality among those five factors [26].

3 Preliminaries

3.1 Underlying Traffic Model

The IDM [12] is regarded as a modern simulation method [21]. However, it sometimes generates unrealistic behavior in cut-in situations (lane changing manoeuvres) [6]. Motivated by this, Kesting et al. [6] proposed an enhanced intelligent driver model (abbreviated as E-IDM) based on IDM, which performs better than IDM and is therefore considered as a modern, advanced traffic simulation method. In this work, we take advantage of the E-IDM as the underlying traffic simulation model.

The IDM considers not only the actual speed v of the current vehicle but also the distance s and the velocity difference Δv between the current vehicle and the leader.

$$a_{idm}(s, v, \Delta v) = a[1 - (\frac{v}{v_0})^{\delta} - (\frac{s^*(v, \Delta v)}{s})^2], \quad (1)$$

where $s^*(v, \Delta v) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}}$, and parameter information can be referred to Table 2.

In order to prevent unnecessarily strong braking reactions due to lane changes, Kesting et al. [6] formulated a constant-acceleration heuristic (CAH) which could obtain an upper limit of a safe acceleration. The CAH is given by

$$a_{cah} = \begin{cases} \frac{v^2 \tilde{a}_l}{v_l^2 - 2s\tilde{a}_l} & v_l(v - v_l) \leq -2s\tilde{a}_l \\ \tilde{a}_l - \frac{(v-v_l)^2 \Theta(v-v_l)}{2s} & \text{otherwise} \end{cases}, \quad (2)$$

where $\tilde{a}_l = \min(a_l, a)$ is the effective acceleration, s is the gap, v and a are the velocity and acceleration of the current vehicle, respectively, v_l and a_l are the velocity and acceleration of the leading vehicle, respectively, and $\Theta(x)$ is the Heaviside step function (only effective when $x > 0$).

$$a = \begin{cases} a_{idm} & a_{idm} \geq a_{cah} \\ (1-c)a_{idm} + & \\ c[a_{cah} + b\tanh(\frac{a_{idm}-a_{cah}}{b})] & \text{otherwise} \end{cases} \quad (3)$$

Kesting et al. [6] combined the IDM and the CAH to obtain an enhanced traffic simulation model—E-IDM, where c is the coolness factor (see Eq. (3)).

3.2 *Lane-Changing Model*

The lane-changing model we use is a simplified gap acceptance model, please refer to [27] for more information. In a gap acceptance model, drivers typically check the feasibility of performing lane changes by comparing the lead and lag gaps to their corresponding critical gaps (minimum acceptable space gaps).

As seen in Figure 1, d_{lead} is the longitudinal distance between the current vehicle and the lead vehicle in the left or right lane, and d_{lag} is the longitudinal distance between the current vehicle and the lag vehicle in the adjacent lanes. d_{lead}^{min} and d_{lag}^{min} are the corresponding minimum acceptable gaps and we set $d^{min} = d_{lead}^{min} = d_{lag}^{min}$ in this study.

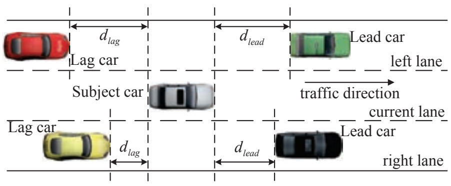


Figure 1: The lead, subject, lag vehicles and the lead, lag gaps in the presented gap acceptance model.

Gap acceptance formulation: $d_{lead} \geq d_{lead}^{min}$ and $d_{lag} \geq d_{lag}^{min}$.

This formulation indicates that the lead and lag gaps are acceptable if they are equal or greater than the corresponding critical gaps, which means the present driver can make a lane change.

We combine the lateral lane-changing behavior with the longitudinal traffic model described above (E-IDM), thus leading to a full traffic model for our simulation.

Table 1: Adjective descriptors for the three personality traits in the PEN model.

Personality Traits	Adjectives
Psychoticism	aggressive,egocentric
Extraversion	active,risk-taking
Neuroticism	tense,shy

Table 2: Ranges of low-level simulation parameters used in this work.

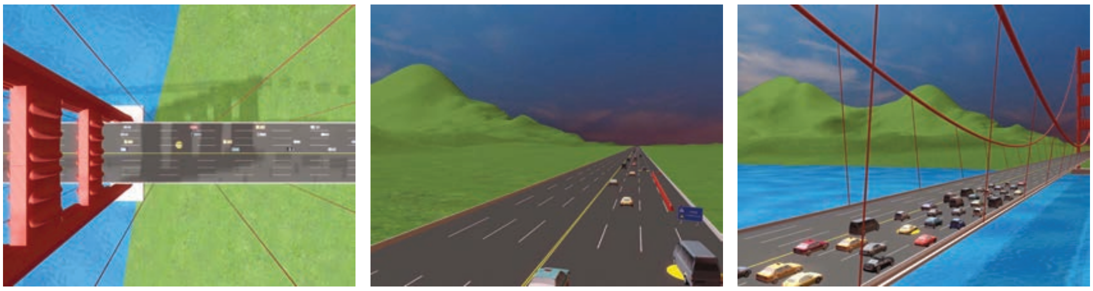
Parameter	Symbol	Min	Max
desired speed	$v_0(m/s)$	25	35
free acceleration exponent	δ	4	4
desired time gap	$T(s)$	1.0	3.0
jam distance	$s_0(m)$	1.0	5.0
maximum acceleration	$a(m/s^2)$	0.5	2.5
desired deceleration	$b(m/s^2)$	1.0	3.0
coolness factor	c	0.99	0.99
minimum acceptable gap	$d^{min}(m)$	5.0	95.0

4 Our Method

4.1 *Perceptual Study for Driving Behaviors*

Variation in low-level simulation parameters influences the perceived behaviors of vehicles in traffic flows. In this section, we conduct a user study to achieve a plausible mapping from low-level simulation parameters to perceived driving behaviors. We carefully select two adjectives for each factor in the PEN model and the adjectives are chosen from EPQ [28] and [29] according to the most common driving behaviors, shown in Table 1. Low-level simulation parameters and the corresponding value ranges are summarized in Table 2. The ranges are set to fully contain the corresponding parameter values in [6].

For the user study, we recruited 50 participants who are between 18 and 50 years old (30% female, 40% drivers). All participants were asked to watch a few video clips generated by computers. Two video clips were played to participants at the same time: one is the reference clip as a baseline for comparison, using the default simulation parameter values for all vehicles; the other clip is generated using ran-



(a) Freeway traffic scenario. (b) Narrowing traffic scenario. (c) Crowded traffic scenario.

Figure 2: Three traffic scenarios.

dom parameter values for marked vehicles and default parameter values for unmarked ones. To be consistent for contrast, the reference video clip is the same in one traffic scenario for all user study questions. After that, participants were asked a few questions, for example, "Do you think the driving behaviors of the marked vehicles in the tested video are more aggressive than that in the reference video?" Participants chose answers on a scale from 1 to 9; "1" denotes totally disagree, "5" denotes either agree or disagree and "9" denotes totally agree.

To gain a wide range of sights, we design three traffic scenarios: freeway traffic, narrowing traffic and crowded traffic (see Figure 2). The first scenario is a freeway traffic, which simulates diverse driving behaviors on freeway. The second is a narrowing traffic scenario, where a section of a lane is under construction and vehicles have to move into other lanes to get through. The last scenario we choose is a crowded traffic scenario, where all vehicles move slowly.

We deliberately select 6 parameters (v_0, T, S_0, a, b and d^{min}) from Table 2, because all of them have an intuitive interpretation [30]. The other two parameters, $\delta = 4, c = 0.99$ are consistent with [6]. To generate a variety of video clips describing high-level driving behaviors, the underlying low-level parameter values (regardless of δ and c) are randomly chosen for the marked vehicles. The marked vehicles in one single clip have the same randomly chosen simulation parameter values, while the unmarked ones share the default simulation parameter values, which are set to be $(min + max)/2$.

Random values are assigned to the simulation parameters in different settings and we generate a total number of 110 video clips for our user study. Each participant is asked to rate the driving behaviors of 6 randomly chosen video clips in each scenario (18 clips in total). Since there are 6 questions for each clip and 18 clips for each participant, we obtain a rich set of 5400 ($6 \times 18 \times 50$) data points.

4.2 Regression Model Training and Validation

Through empirical analysis of the user study data, we find that there exists a linear or nonlinear regression between perceived behaviors and low-level simulation parameters. To find an optimal regression model, we use the collected data to train and test different models. Four regression models are chosen: *Multiple Linear Regression* (MLR), *Polynomial Regression* (PR), *Gaussian Process Regression* (GPR) and *Support Vector Machine Regression* (SVMR). We use 80% of the collected data to train different regression models. The rest 20% data is retained for validation, to determine which is the best regression model among all the trained models.

For the sake of completeness and readability, we present the relationship in a concise way (see Eq. (4)). The value ranges of the six adjectives and the three PEN factors are $1 \sim 9$.

$$y = f(\mathbf{X}), \tag{4}$$

where y indicates one of the six adjectives or one of the three PEN factors, and $\mathbf{X}$ is a vector concatenating v_0, T, s_0, a, b and d^{min}.

After training these four regression models, we utilize them to make predictions with the retained 20% test data, respectively. And then we do some comparisons between the predicted data and the real data by computing their mean

Table 3: The mean square error (MSE) and the normalized root mean square error (N-RMSE) between the predicted data and the real data for 4 different regression models.

Regression Model	MSE	NRMSE
MLR	0.9123	0.1588
PR	1.4839	0.2028
GPR	1.8532	0.2826
SVMR	2.0624	0.2982

square error (MSE) and the normalized root mean square error (NRMSE), and finally pick out the optimal regression model. The NRMSE is computed by Eq. (5), where $y_{max} - y_{min}$ is the range of observed values of the dependent variable being predicted. Table 3 shows the MSE and the NRMSE between the predicted data and the real data for different regression models.

$$NRMSE = \frac{\sqrt{MSE}}{y_{max} - y_{min}} \tag{5}$$

As observed from Table 3, the best fitting model is the MLR model. With any given simulation parameters, the MLR model allows us to compute the corresponding values of high-level behaviors (six adjectives and three PEN traits), thus being capable of predicting related driving behaviors.

With the MLR model, we obtain the linear mapping β_{adj} between the 6 adjective descriptors and the low-level simulation parameters.

$$\beta_{adj} = \begin{pmatrix} 6.39 & 6.40 & 4.73 & 6.20 & 4.05 & 2.90 \\ 0.03 & 0.02 & 0.06 & 0.05 & -0.04 & -0.04 \\ -0.77 & -0.50 & -0.35 & -0.66 & 0.67 & 0.86 \\ -0.10 & 0 & -0.05 & -0.10 & 0.04 & 0.15 \\ 0.21 & 0.04 & 0.17 & 0.10 & -0.17 & -0.29 \\ 0.10 & 0.19 & 0.07 & 0.04 & -0.05 & 0.02 \\ -0.03 & -0.03 & -0.01 & -0.03 & 0.01 & 0.02 \end{pmatrix}$$

In a similar way, we also derive a linear mapping β_{pen} for the PEN model. Two adjectives are mapped to one corresponding factor of the model, shown in Table 1.

$$\beta_{pen} = \begin{pmatrix} 6.39 & 5.47 & 3.48 \\ 0.02 & 0.05 & -0.04 \\ -0.63 & -0.51 & 0.77 \\ -0.05 & -0.07 & 0.09 \\ 0.13 & 0.13 & -0.23 \\ 0.15 & 0.06 & -0.02 \\ -0.03 & -0.02 & 0.02 \end{pmatrix}$$

Table 4: Sampled simulation parameters for six adjectives and three PEN traits.

Personality Traits	v_0	T	s_0	a	b	d^{min}
aggressive	33	1	3	2.5	1	9
egocentric	30	2	3	2.5	3	13
active	30	1	4	2.5	3	36
risk-taking	34	2	2	2.5	1	8
tense	26	3	4	1	2	63
shy	27	3	5	0.8	3	79
Psychoticism	31	2	3	2.1	2	10
Extraversion	33	2	2	1.8	1	16
Neuroticism	28	3	4	0.6	3	78

5 Results

With the computed mappings, we can simulate traffic which exhibits high or low levels of the six personality adjectives, or the three PEN factors. To be consistent, we limit all six simulation parameters within their corresponding ranges. Probably there are a few groups of parameters for a single adjective and we just choose one sample for each adjective in this work, shown in Table 4.

5.1 Simulation Results

Scenario 1 is a freeway situation, in which rich driving behaviors are observed, and we show the trajectories and velocities of the marked vehicular agents with different personalities in Figures 3 and 4, respectively.

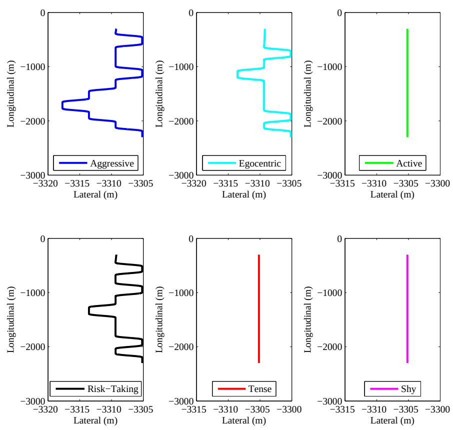


Figure 3: The trajectories of vehicular agents with different personalities.

Aggressive agents usually make invasive behaviors and an important way is frequently changing lanes. Egocentric agents, which are less aggressive than aggressive ones, typically try to find benefits by inserting themselves into some place wherever there is room. Risk-taking agents often do things full of danger, with less consideration about their own and others' situations. Active agents often do things actively: accelerating, decelerating, overtaking, changing lanes or other behaviors with considering their own conditions and the surrounding environments. Tense and shy agents always strictly move along a single lane and hardly perform lane changing, thus leading to more smooth velocity variations (Figure 4) and a longer interval (see the supplementary video).

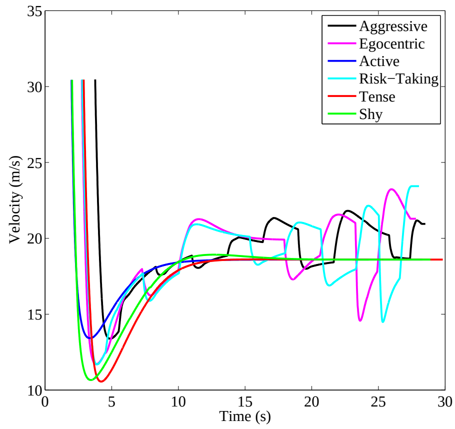


Figure 4: The velocity variations of vehicular agents with different personalities.

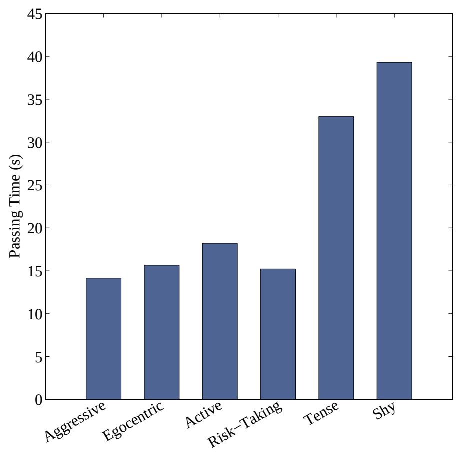


Figure 5: The passing times of vehicular agents with different personalities.

Scenario 2, a specially designed traffic situation, in which vehicular agents with different traits exhibit diverse behaviors. Figure 5 illustrates the passing times of agents with different traits: aggressive agents, having the shortest passing time, is the fastest to get through, while tense and shy agents are the slowest to pass through the *under construction section* since they keep a longer distance from the leading vehicles and move less quickly.

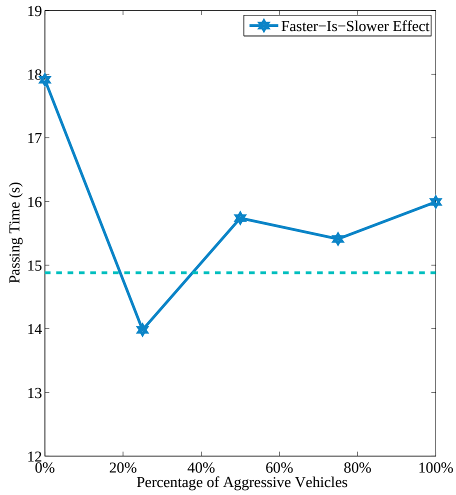


Figure 6: The faster-is-slower effect (see text).

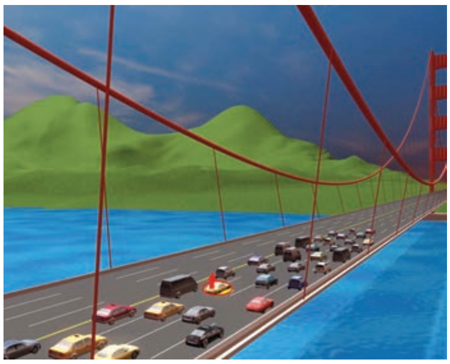


Figure 7: The sticking-in-a-pin-wherever-there-is-room effect (see text).

We also observe the emergent *faster-is-slower effect* [31] when the percent of aggressive agents grows. The passing time becomes longer when the percent of aggressive agents exceeds a critical threshold (see Figure 6). This effect is typically related with impatience: aggressive agents always perform impatient behaviors. When there are a few aggressive agents in the narrowing traffic scenario, they will seize the opportunity to quickly pass through the *under construction section*. However, when the percent of aggressive agents exceeds a threshold, they fight with each other and then the clogging appears, thus leading to the increase of the passing time.

In scenario 3, all vehicles encounter a traffic congestion: tense and shy agents may cut speed slowly when there is a long gap, while aggressive and risk-taking ones may decelerate more suddenly at a short interval. We also find the *sticking-in-a-pin-wherever-there-is-room effect*: some vehicular agents are egoistical and always try to insert themselves into positions wherever there is space. As shown in Figure 7, the red arrow indicates the car surrounded by a red ellipse is moving from one lane to another to insert itself into a new position, even there is a little space.

5.2 *Heterogeneous Traffic*

Using the derived mappings from the MLR model, we are capable of generating different traffic behaviors in simulation, thus leading to heterogeneous traffic. Here, we apply our method to an urban scene, shown in Figure 8. Different colors are assigned to vehicular agents by their personality traits, as an example, agents with red color are aggressive. Please see animation results in the supplementary video.

Figure 8: Simulating heterogeneous traffic by adapting our method to an urban scene. Vehicles with different colors have different kinds of personality traits.

5.3 *Performance Statistics*

Strictly speaking, our technique is a data-driven approach. The user study data can be processed in advance, therefore, our method does not add extra cost to the execution time of simulations.

Table 5: Timing results for all traffic scenarios.

Scenarios	Vehicles	Faces	FPS (s^{-1})
Freeway Traffic	60	1446949	659.433
Narrowing Traffic	56	838660	505.895
Crowded Traffic	45	1572782	589.857
Urban Traffic	459	4372694	285.440

All the timing results were collected on an Intel Core(TM) i7-3770 3.40-GHz CPU with a GeForce GTX 670 graphics card. The runtime results of different traffic scenarios are shown in Table 5.

5.4 *Evaluation Study*

To validate and evaluate our approach, we also conducted an additional user study. New video clips were created in this study to reduce bias. It involved 27 participants (ages 18 to 45, 12 female and 15 male). The participants randomly selected a pair of clips, one using the sampled simulation values in Table 4 and the other using the default values. Compared with the reference clip, the participants were asked to choose which traits the other clip better exhibits. Note that before asking questions, the three factors in the PEN model were explained concisely and explicitly to the participants.

We classified all the answers and calculated the pearson correlation coefficients between users' answers and the model's predictions. Furthermore, to demonstrate that the results were not induced by accident, we also computed the correlation coefficients' significance. p is the two-tailed probability and $1 - p$ is the significance. Please see Figure 9. The high correlation coefficients, as well as the high significance for five adjectives (> 0.95) and three PEN traits (> 0.99), validate the strong correlations between participants' perception and the model predictions. Therefore, this study demonstrates the effectiveness and usefulness of our method.

6 Conclusion

In this paper, we have presented a novel approach to simulate heterogeneous traffic by

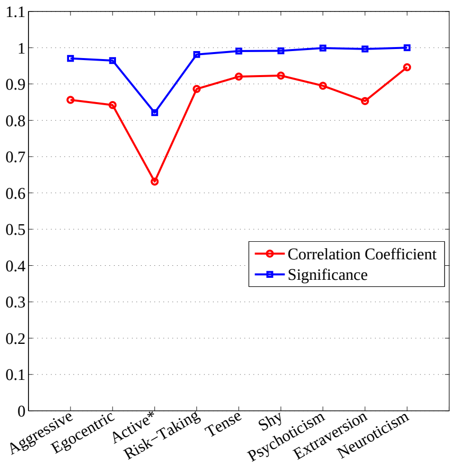


Figure 9: The correlation coefficients between the participants' answers and the model's predictions for all traits, and the corresponding correlation coefficients' significance. * denotes non-significantly correlated ($p > 0.05$).

training an optimal regression model between low-level simulation parameters and high-level personality traits. Our method is able to create unhomogeneous traffic, where vehicular agents exhibit high or low levels of the six adjectives (aggressive, egocentric, active, risk-taking, tense and shy) and the three PEN traits (Psychoticism, Extraversion, Neuroticism).

To the best of our knowledge, our parameter-to-personality approach is the first-of-its-kind method to animate traffic behaviors with various personality traits. Our method allows users to be relieved from tedious and time-consuming work—manually tuning traffic simulation parameters. It should be noted that the default parameter values for the baseline video clips could be chosen in various ways, and our aim is to enable an easy comparison between the default video clips and the other video clips. The results in our work show the average form is a decent choice. Our method is not only limited to the E-IDM traffic model, it can also be straightforwardly extended to other microscopic traffic models, but needs to derive new mappings between traffic behaviors and new simulation parameters.

Some limitations exist in our current approach. First of all, computer-generated video clips for user study may be deficient. Probably we can combine this with real-world traffic video clips, which can display more rich, intuitive and realistic behaviors. Moreover, a more precisely trained model may be sought out if we find more adjectives.

The future work would be focused on combining real-world traffic video with our current framework and exploring the applicability of our method in real-world traffic. We would like to find more adjective descriptors to more accurately depict high-level traffic behaviors. Another interesting direction we would also like to pursue is to train an optimal regression model from traffic simulation parameters to other trait theories (e.g. the CANOE model).

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