A Heterogeneous Visual Imaging Model for Analyzing the Impact of Vehicle Type on Car-Following Dynamics

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ABSTRACT

Heterogeneity is an essential characteristic in car-following behaviors, which can be defined as the differences between the car following behaviors of driver/vehicle combination under comparable conditions. This paper proposes a Visual Imaging Model (VIM) with relaxed assumption on a driver's perfect perception for 3-D traffic information and uniform reaction to vehicles with different sizes in most existing car following models. The proposed model can generate greater stimuli to the followers from the leading vehicles with larger back sizes (i.e. defined as vehicle width×vehicle height) and short distance to the following vehicles, but less changes in stimuli for the distant leading vehicles under various back sizes. The US101 NGSIM data set containing vehicle type/size information is used to evaluate the proposed model at the levels of single trajectory pair and vehicle types. The calibration and validation results show the promising performance of the proposed model in describing heterogeneous car-following behavior. In this study, it is also found from US101 NGSIM data set that in relatively high velocity range, the following gap distance for car following truck (C-T) is greater than that for car following car (C-C), while in low velocity range, C-T has a smaller spacing than C-C. The phenomenon can also be reproduced by the proposed model.

INTRODUCTION

Heterogeneity is an essential characteristic in car following behaviors and can be defined as the differences between the car following behaviors of driver/vehicle combination under comparable conditions (*1*). The heterogeneous driving behavior studies usually include three aspects of the general problem: different driving styles within a vehicle group of the same vehicle type, different driving styles related to the different vehicle types, different driving styles of the follower because of the leader's different vehicle type. Ossen and Hoogendoorn (*1*) gained insights into the level of heterogeneity in car following behaviors in real traffic under different types of heterogeneity. In another study (*2*), they pointed out the highly different driving styles in car following behavior observed in a vehicle trajectory dataset collected from a helicopter and also explored the feasibility of incorporating different types and degree of heterogeneity in car following models. Ranjitkar et al.(*3*) investigated the performance of some well-known microscopic traffic flow concepts based on different GPS data and found that interpersonal variation are relatively higher than the intermodal variations. Punzo and Tripodi (*4*) extend the single-class models to multiclass traffic scenario and developed a calibration procedure for multiclass GIPPS car-following model. Meanwhile, several researchers have concentrated on the following distance with respect to the vehicle type. The following distance for car following truck (C-T) was found to be smaller than that for car following car (C-C) in several different data sets (*5,6,7*). However, Yoo and Green (*8*) obtained different conclusions that the following distance of C-C was 10% less than that C-T. Ravishankar and Mathew (*9*) also concluded that the mean following distance varied across vehicle-type combinations with smaller sized vehicles following at a closer spacing. The contradicting results obtained by previous researchers about the following gap distances for C-C and C-T indicate the necessity of studying the problem from a different viewpoint.

However, most existing car-following models were postulated for drivers' perfect perception about 3-D traffic information (velocity, distance or acceleration) and homogenous vehicle types. For example, the well-known General Motors (GM) model, firstly proposed by Chandler et al. (*10*), utilizes the relative velocity between the leader and the follower as the stimulus. Safe distance (SD) models pursue a safe following distance so as to avoid the rear-end collision, one representative of which is Gipps' model (*11*). Optimal Velocity Model (OVM) employs the difference between the current velocity and ideal velocity dependent on the distance headway as the stimulus (*12*). Despite their success in describing the motion of individual vehicles in continuous space and time from different aspects, there are some deviations between the car-following behaviors described in those models and the reality. 1) Car following behavior is a human decision-making and response process, and drivers can not accurately perceive the 3-D traffic information, which violates the basic assumption of those models. 2) Such car-following models do not have built-in mechanism to describe the heterogeneous traffic flow composed of vehicles with different vehicle types. Multiple sub-models with different model parameters need to be developed and calibrated to describe each heterogeneous car-following scenario. However, it should be noted that Action Point (AP) models set some perceptual thresholds of spacing or relative velocity to define the minimum value of the stimulus to which the driver will react (*13,14,15,16,17*). Especially drivers' perceiving the relative velocity between two successive vehicles is usually through changes on the visual angle subtended by the vehicle in-front, which is definitely related to the vehicle type/size of the preceding vehicle (*15*). Therefore, AP models can remedy above two deviations in some degree.

Moreover, many other researchers have also considered different kinds of projected 2-D visual information related to the vehicle type/size of the preceding vehicle when modeling the car following behaviors, which can all be utilized to cope with the heterogeneous driving behaviors due to the vehicle type/size. For example, Andersen and Sauer (*18*) presented Driving by visual angel (DVA) model based on the framework of Helly's model (*19*), which can produce more predictive driving performance than other models based on 3-D information. Jin et al.(*20*) introduced a visual angle car following model by using the visual angle and its change rate, which contributes to the design of more realistic car following models. Lee and Jones (*21*) proposed a model that determines acceleration by the change rate of the visual angle. On the other hand, Lee (*22*) showed that the inverse rate of expansion of an approaching object (i.e. Denoted by τ) was a visual variable that could be used to estimate the time to an impending collision, which was also investigated in the studies of driving performance (*23,24*). However, when traffic flow is stable, τ usually keeps at an infinite value. Therefore, it has limited usefulness in actual car following.

Besides, what worth our attention is that another candidate visual source is the visual image information, which is related to two-dimensional information about the back size of the leading vehicle. Michael (*25*) suggested that the image size of the preceding vehicle or its visual extent could be used to model car following. Moreover, Zielke et al.(*26*) designed a computer algorithm for car following so as to maintain a constant image size of the preceding vehicle. Therefore, inspired by using the image information as the stimulus, in this paper, we utilize the visual imaging size of the leading vehicle and its change rate to replace the gap distance and relative velocity and propose the visual imaging model (abbreviated as VIM) based on the framework of Helly's model. The proposed VIM can not only relax the unrealistic assumption on a driver's perfect perception for the 3-D traffic information, but also can describe the heterogeneous driving behaviors caused by the various vehicle-type of the leader. The rest of the paper is organized as follows. First, VIM is proposed and analyzed. Then heterogeneous driving behaviors under different leader-follower compositions and velocity ranges are analyzed based on the US101 NGSIM data. After that, the rationality and performance of VIM in modeling the heterogeneous driving behaviors are evaluated. Finally, some important conclusions are drawn.

NEW VISUAL CAR FOLLOWING MODEL

The Proposed Visual Imaging Model

Existing vision based car-following models (*15-21*) usually approximate visual angles as the width of the leading vehicle divided by the gap distance, which only employs one-dimensional information of the leading vehicle (i.e. the vehicle width) and cannot effectively describe the stimulus to the follower from the back size of the leading vehicle. From the viewpoint of the visual imaging process, two-dimensional vehicle size information (i.e. the vehicle width and length) needs to be considered and incorporated into the modeling of the heterogeneous driving behaviors due to the leader's vehicle type.

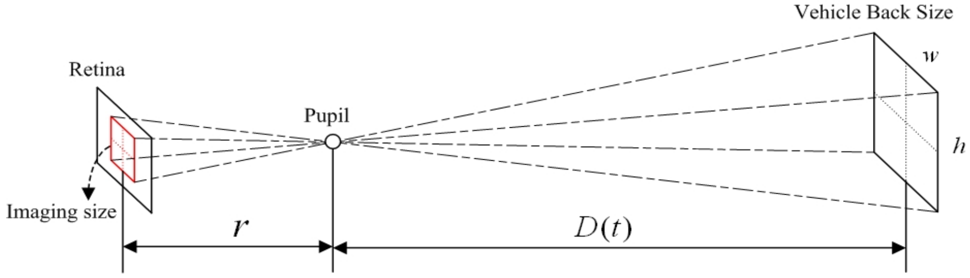


FIGURE 1 Illustration of the visual imaging

According to the principle of visual imaging (cf. Figure 1), the back of the leading vehicle is projected on the retina of the following driver, therefore under the same gap distance (denoted by $D(t)$) a leading vehicle with the lager back size will result in greater image size and cause stronger stimulus to the follower, which can be expressed as

$$w/D(t) = w'/r \tag{1}$$

$$h/D(t) = h'/r \tag{2}$$

$$L_S/D(t)^2 = L_S'/r^2 \tag{3}$$

where w and h are the width and height of the leading vehicle respectively, w' and h' are the imaging width and height of the leading vehicle, r is the diameter of the eye, $L_S = w \cdot h$ is the back size of the leading vehicle, $L_S' = w' \cdot h'$ is the visual imaging size of the leading vehicle.

Moreover, Helly's model (*19*) can be served as the framework for VIM, which consists of a linear combination of a distance headway maintenance factor with a relative velocity-minimizing factor. The model ensures only when the desired distance headway has been achieved and the velocity difference is zero, the acceleration output is zero. After substituting the information of distance headway and relative velocity in Helly's model with appropriate factors related to visual information, similar stimuli in VIM come from two sources. One is the difference between the current and desired visual imaging size (i.e. maintenance factor). The other is the change rate of the visual imaging size (i.e. the minimizing factor). Besides, only when the desired visual imaging size has been reached, and the change rate of visual imaging size is zero, the acceleration output becomes zero. Therefore, the formulation of VIM can be expressed as

$$a(t) = m \cdot [S_d(t) - S(t)] + n \cdot dS(t)/dt \tag{4}$$

where $S_d(t) = L_S \cdot r^2 / D_d(t)^2$ and $S(t) = L_S \cdot r^2 / D(t)^2$ indicate the desired and current visual imaging size of the leading vehicle respectively, $m > 0$ and $n < 0$ are the sensitivity coefficient, $D_d(t)$ is the desired gap distance between two successive vehicles and can be formulated as

$$D_d(t) = \begin{cases} t_d \cdot v_f, v_f \geq v_j \\ s_0, v_f < v_j \end{cases} \tag{5}$$

where t_d is the desired time gap, v_f is the velocity of the following vehicle, s_0 is the gap distance in the traffic jam state, v_j is the critical velocity used to distinguish the traffic jam state. VIM model can then be rewritten as

$$a(t) = m \cdot [\frac{r^2 \cdot L_S}{D_d(t)^2} - \frac{r^2 \cdot L_S}{D(t)^2}] + n \cdot \frac{d}{dt}[\frac{r^2 \cdot L_S}{D(t)^2}] \tag{6}$$

According to equation (6), the stimuli in VIM include two parts. One is the difference between the desired and current visual imaging size of the leading vehicle, which can be expressed as

$$c_d = \frac{r^2 \cdot L_S}{D_d(t)^2} - \frac{r^2 \cdot L_S}{D(t)^2} \tag{7}$$

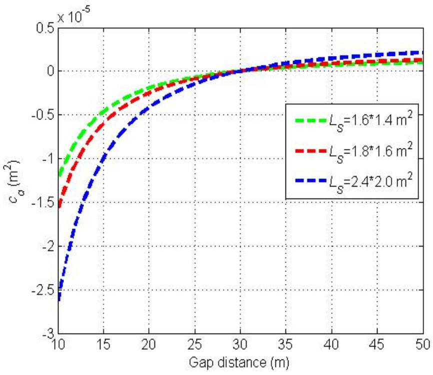
The other is the change rate of visual imaging size formulated as

$$c_r = \frac{d}{dt}[\frac{r^2 \cdot L_S}{D(t)^2}] = \frac{-2r^2 \cdot L_S \cdot \Delta V}{D(t)^3} \tag{8}$$

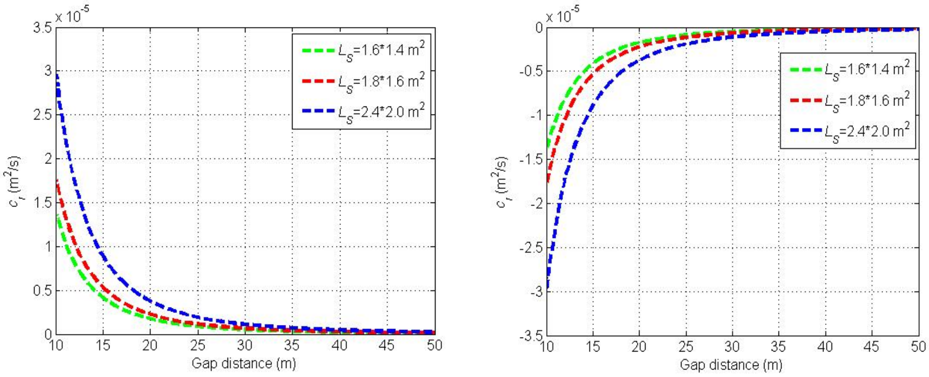
where the relative velocity $\Delta V = v_l(t) - v_f(t)$, $v_l(t)$ is the velocity of the leading vehicle.

Performance Analysis of Visual Imaging Model

In order to understand the heterogeneous responses of the follower influenced by the leader's vehicle type, Figure 2(a) illustrates the relationship of the maintenance factor c_d and gap distance versus various L_S and Figure 2(b-c) shows the relationship between minimizing factor c_r and gap distance under different L_S.



(a)



(b) (c)

FIGURE 2 Relationship between driver response and the gap distance under different L_S. r=2.5*10-2m, (a) t_d=2s, v_f=15m/s, v_j=3m/s,(b) ΔV=-5m/s, (c) ΔV=5m/s

In Figure 2(a) when the current gap distance $D(t)$ is smaller than the desired gap distance $D_d(t)$ (30 m), the difference between the desired and current visual imaging size of the leading vehicle (i.e. c_d) is negative, which means the follower has to decelerate to maintain the desired visual imaging size. Meanwhile, under the same current gap distance the larger L_S would result in greater absolute value of c_d. When $D(t)>D_d(t)$, c_d becomes positive, which means the following vehicle need to accelerate to keep the desired visual imaging size, and larger L_S results in greater c_d under the same gap distance. It should be noted that when $D(t)<<D_d(t)$, the difference of c_d under various L_S can be observed clearly because the driver can easily identify back size of the leading vehicle. On the other, when $D(t)>>D_d(t)$, such difference is remarkably small because of the driver's difficulty in distinguishing the visual imaging size of the leading vehicle.

In Figure 2(b),when $\Delta V<0$ the following driver will brake to maintain the visual imaging size, that is, to minimize the relative velocity with the preceding vehicle. Therefore, the value of c_r is positive (Note: n<0). Correspondingly in Figure 2(c), when $\Delta V>0$the follower needs to accelerate and the value of c_r is negative. Meanwhile, Figure 2(b-c)also illustrates that under the same gap distance, the absolute value of c_r is larger when the leading vehicle has larger L_S. Meanwhile, compared with the situation of small gap distance, the value of c_r under different L_S has insignificant change when $D(t)$ is relatively larger, which reflects that the driver has difficulty in recognize the change of the visual imaging size when the leading vehicle is extremely distant.

VALIDATION OF THE HETEROGENEITY

Field Data Preprocessing

It should be noted that there are some recording errors in the NGSIM data (*27*), e.g. the values of acceleration or deceleration are unusually large, and the gap distance between two successive vehicles is not larger than zero. Those errors should be removed before the further selection of NGSIM data. Moreover, in order to detect the "close following" behaviors from NGSIM data, the gap headway (in seconds) is used to describe the time gap from the rear of the leading vehicle to the front of the following vehicle and the smaller time gap means the closer car following behaviors. According to the characteristics of the NGSIM data, a value of 3s for the gap headway (as also used by Sayer et al. (*6*) and Bennett (*28*)) has been chosen as the critical gap headway for "close following" behavior. Then the extracted vehicle trajectory data with the characteristic of "close following" can be further separated into different groups according to the leader-follower composition (e.g. C-C and C-T) and velocity range (e.g.10<=V<20 (km/h), 20<=V<30 (km/h), 30<=V<40 (km/h), 40<=V<50 (km/h) and 50<=V<60 (km/h)). Note: the velocity range here is divided based on the averaged velocity of the following vehicle and each pair of leader-follower trajectories usually lasts for about 30 seconds. Finally, the averaged mean gap distance (MGD) can be calculated for each group. It should be noted that the gap distance is obtained based on NGSIM data by eliminating the vehicle length according to the composition of C-C or C-T.

Statistical Results

From the statistic results in table 1, it can be observed that the averaged MGDs for C-C are significantly different from those for C-T except within the velocity range of 20<=V<30 (km/h). For the velocity range 10<=V<20 (km/h), the averaged MGD for C-C is larger than that for C-T, which is the opposite for the averaged MGD of C-C and C-T within the velocity range of 30<=V<40, 40<=V<50 or 50<=V<60 (km/h). Furthermore, the unpaired *T*-test is used to check whether the averaged MGD for C-C in each velocity range is significantly different from that for C-T in the general case. That is, if $|t|>t_{0.05}\,(N_{\text{C-C}}-1+N_{\text{C-T}}-1)$, the averaged MGD for C-C is significantly different from that for C-T generally; otherwise, it is not significantly different from each other in the general case, where $N_{\text{C-C}}$ and $N_{\text{C-T}}$ are respectively the number of leader-follower trajectory pairs for C-C and C-T

TABLE 1 Statistic Results from Field Data US101

Velocity Range(km/h)	C-C		C-T		*T*-test	
	$N_{\text{C-C}}$	Averaged MGD (m)	$N_{\text{C-T}}$	Averaged MGD (m)	*T* values	*P*-values
[10,20)	284	8.7990	3	5.8734	$\lvert t\rvert=2.2160$	$\lvert t\rvert>t_{0.05}$ (285)
[20,30)	722	12.2060	21	11.9774	$\lvert t\rvert=0.2796$	$\lvert t\rvert<t_{0.05}$ (741)
[30,40)	1067	15.0525	38	16.3884	$\lvert t\rvert=1.6533$	$\lvert t\rvert>t_{0.05}$ (1103)
[40,50)	453	17.3598	49	20.7709	$\lvert t\rvert=4.0069$	$\lvert t\rvert>t_{0.05}$ (500)
[50,60)	29	20.7017	28	25.1970	$\lvert t\rvert=2.0537$	$\lvert t\rvert>t_{0.05}$ (55)

From table 1, it is concluded that in the relatively low velocity range, e.g. 10<=V<20 (km/h), the averaged MGD for C-T is significantly smaller than that for C-C. However, in the relatively high velocity ranges, e.g. 30<=V<40, 40<=V<50 and 50<=V<60 (km/h), the averaged MGDs for C-T become significantly larger than those for C-C. Meanwhile, it should be noted that when the velocity range is 20<=V<30 (km/h), the averaged MGD for C-C is not significantly different from that for C-T. Therefore, it is easily known that in the relatively high velocity range, the follower is willing to keep a larger gap distance with the preceding truck to allow sufficient visual clearance for safe driving, which is completely different from that situation in the low velocity range. The cause can be analyzed empirically as follows: the leading truck with the higher velocity will produce more safety concerns to the follower than the leading car, which is because of the driver's different visual perception to the stimulus of the moving back size of the leading truck in various velocities.

VISUAL IMAGING MDOEL EVALUATION WITH NGSIM DATA

Evaluation Method

The averaged MGD for each group of vehicle trajectories can be utilized to determine the rationality of VIM in reproducing the heterogeneous driving behaviors. Meanwhile, for each pair of vehicle trajectories, Mean Absolute Relative Error (i.e. MARE) and Mean Absolute Error (MAE) are used to measure the difference between actual and simulated results during calibration, which take the following forms.

$$MARE = \frac{\sum_{t=1}^{T} \left| h^{sim}(t) - h^{data}(t) \right| / h^{data}(t)}{T} \tag{9}$$

$$MAE = \frac{\sum_{t=1}^{T} \left| h^{sim}(t) - h^{data}(t) \right|}{T} \tag{10}$$

where $h^{sim}(t)$ is the simulated distance headway at time *t*, $h^{data}(t)$ is the actual distance headway from the field data at time *t* and T is the sample time.

Meanwhile, in order to facilitate the calibration of VIM, equation (6) can be rewritten as

$$a(t) = p \cdot [\frac{L_S}{D_d(t)^2} - \frac{L_S}{D(t)^2}] + q \cdot \frac{d}{dt}[\frac{L_S}{D(t)^2}] \tag{11}$$

where $p = m \cdot r^2$ and $q = n \cdot r^2$ denote the constant coefficients. Thus, the parameters to be calibrated include p, q, t_d and s_0. Besides, the vehicle back size L_S can be adjusted according to the leader's actual vehicle type.

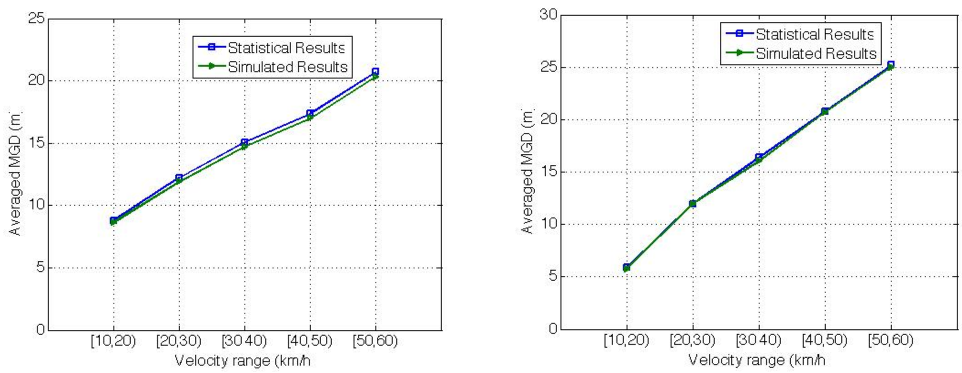
Single Trajectory Pair Based Evaluation

The simulation processes are as follows. At the first step, model parameters of VIM are calibrated using Genetic Algorithm (GA) Toolbox in Matlab for each pair of leader-follower trajectories. At the second step, the calibrated model reproduces the trajectory of the following vehicle. Then at the third step, we calculate the MGD, MARE, and MAE. The three steps are repeated for each group of vehicle trajectories to obtain the Averaged MGD、Averaged MARE、Averaged MAE and Variance of MAE (VMAE)for C-C and C-T within different velocity ranges (cf. Table 2).

TABLE 2 Numerical Results by VIM Based on Field Data from US101

	Velocity Range (km/h)	[10,20)	[20,30)	[30,40)	[40,50)	[50,60)
C-C	Averaged MGD (m)	8.6162	11.8826	14.7217	16.9896	20.3134
	Average MARE (%)	8.34%	7.83%	7.51%	6.83%	6.85%
	Averaged MAE (m)	0.3203	0.4545	0.5029	0.5515	0.6238
	VMAE	0.0888	0.2202	0.3342	0.3565	0.4292
C-T	Averaged MGD (m)	5.7544	11.9596	16.0330	20.7219	24.9656
	Average MARE (%)	3.45%	5.18%	4.69%	3.55%	1.46%
	Averaged MAE (m)	0.1253	0.3046	0.4209	0.3029	0.2924
	VMAE	0.0436	0.0960	0.2520	0.1479	0.3123

Note: for C-C the proper L_S=1.8*1.6 m^2; for C-T the proper L_S=2.4*2.2 m^2.



(a) (b)

FIGURE 3 Comparison of averaged MGD in different velocity ranges.
(a) C-C, (b) C-T.

In table 2, the simulated results show that the averaged MAREs are all smaller than 10%, averaged MAEs do not exceed one meter and VMAEs are also within a small range, which illustrate the capability of VIM in reproducing the heterogeneous driving behaviors under different situations. Meanwhile, figure 3 demonstrates that under each group of vehicle trajectories, averaged MGDs simulated by VIM are consistent with the statistical results in table 1, which further verifies the performance of VIM in simulating the heterogeneous car following behaviors.

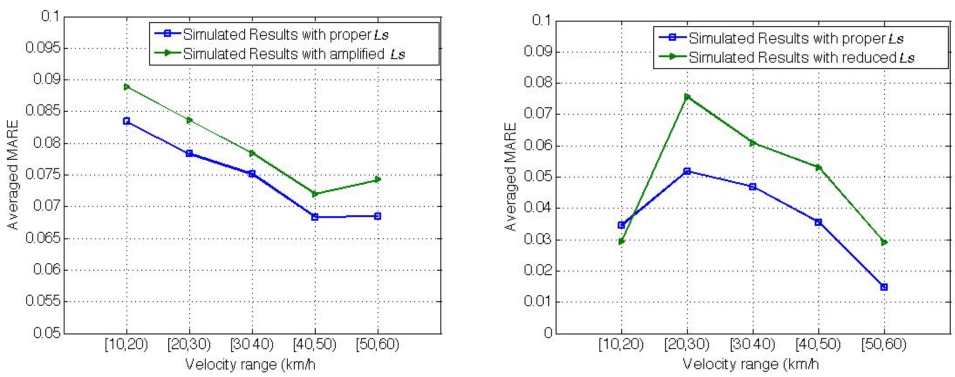
Cross Comparison with Different L_S

In VIM, L_S denotes the back size of the leading vehicle and is a parameter dependent on vehicle types. Therefore, VIM can directly capture the heterogeneous driving behaviors influenced by the leader's vehicle type. In order to check the rationality of incorporating L_S into VIM, the trajectory reproducing tests are repeated with different Ls values. Table 3 shows that although L_S is amplified or reduced, averaged MAREs are still below 10% and averaged MGDs are all close to simulation results in table 2. However, figure 4 illustrates that averaged MAREs produced by VIM with proper L_S are usually smaller than those by VIM with amplified or decreased L_S. This demonstrates the necessity of selecting appropriate L_S in VIM according to the leader's actual vehicle type.

TABLE 3 Cross Comparison Results by VIM Based on Field Data from US101

	Velocity Range (km/h)	[10, 20)	[20, 30)	[30, 40)	[40, 50)	[50, 60)
C-C	Averaged MGD with amplified L_S(m)	8.6085	11.8181	14.5456	16.6529	19.7710
	Averaged MARE (%)	8.89%	8.36%	7.84%	7.20%	7.42%
C-T	Averaged MGD with reduced L_S (m)	5.9117	12.4262	16.7031	21.5760	25.7316
	Averaged MARE (%)	2.93%	7.56%	6.09%	5.30%	2.89%

Note: for C-C the amplified L_S=1.9*1.8 m^2; for C-T the reduced L_S =1.8*1.6 m^2.



(a) (b)

FIGURE 4 Comparison of MAREs in various velocity ranges. (a) C-C, (b) C-T.

Vehicle Type Based Evaluation

In order to evaluate the performance of VIM, two well-known car-following models based on 3-D traffic information (i.e. Optimal Velocity Model (OVM) and Intelligent Driver Model (IDM)) and one model utilizing visual angle information (i.e. Driving by Visual Angle Model (DVA)) are used as the reference models for comparison (See **Appendix A**). Different from single trajectory pair based evaluation where model parameters are calibrated for each pair of car-following trajectories, in the vehicle type based evaluation, only one set of parameters is calibrated for C-C and C-T respectively. The detailed processes can be described as follows.

Firstly, any pair of leader-follower trajectories that lasts for about 30 seconds should be selected from US101 data and distributed into the corresponding group based on its leader-follower composition, e.g. C-C or C-T; At the second step, with regard to each group of leader-follower trajectories, one set of model parameters are calibrated respectively for VIM、OVM、IDM and DVA by Genetic Algorithm (GA) Toolbox in Matlab; Thirdly, these four calibrated models are validated by the other different group of leader-follower trajectories, which can also be called cross-validation; Finally, the calibration and validation results both denoted by MAREs can be utilized to compare the predicting performance of these four models.

TABLE 4 Calibration and Validation Results by Different Models

	VIM		OVM		IDM		DVA	
Calibration (C-C data)	MARE t_d[s] p[1] q[1] s_0[m]	20.95% 1.3534 342.61 -29.423 4.4985	MARE α [s^{-1}] V_1[m/s] V_2[m/s] C_1[m^{-1}] C_2[1]	22% 1.0587 1.6648 12.86 0.2187 1.7382	MARE v_0[m/s] s_0[m] T[s] a[m/s^2] b[m/s^2] δ[1]	35.28% 35.788 3.8538 0.2273 9.1451 0.3890 16.114	MARE t_d[s] j[1] k[1]	63.28% 0.3627 2.1762 -0.1011
Validation (C-T data)	MARE	13.93%	MARE	14.28%	MARE	23.84%	MARE	45.69%
Calibration (C-T data)	MARE t_d[s] p[1] q[1] s_0[m]	13.97% 1.4980 339.59 -1.1157 3.5065	MARE α [s^{-1}] V_1[m/s] V_2[m/s] C_1[m^{-1}] C_2[1]	14% 0.6460 4.9176 10.151 0.2955 2.9622	MARE v_0[m/s] s_0[m] T[s] a[m/s^2] b[m/s^2] δ[1]	22.76% 93.635 2.0259 0.0424 7.1418 0.2158 12.469	MARE t_d[s] j[1] k[1]	41.29% 0.5737 0.2482 -3.6040

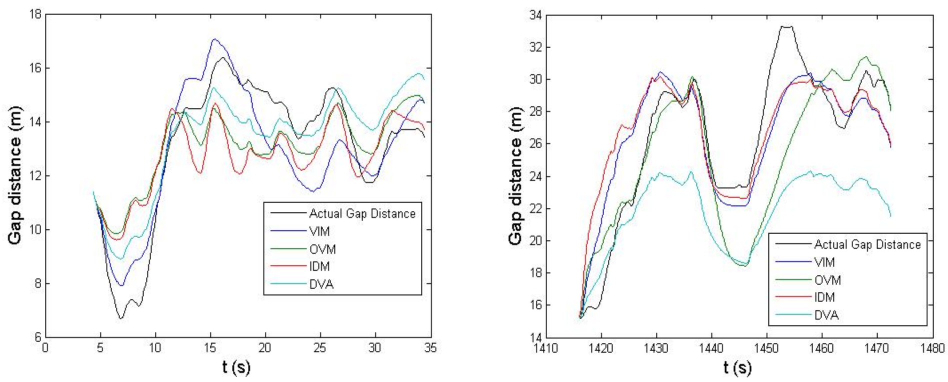
Validation (C-C data)	MARE	22.51%	MARE	22.71%	MARE	38.17%	MARE	55.88%

Note: the number of the pair of leader-follower trajectories for C-C is 2556 and that for C-T is 154.

Results in table 4 show that MAREs generated by VIM during the processes of calibration and validation are smaller than those obtained by other three reference models, which not only implies the better predictive performance of VIM in calibration process but also illustrates the better adaptability of VIM in validating the heterogeneous driving behaviors through adjusting the parameter about the back size of the leading vehicle.

Moreover, the performance of these four models can also be further evaluated by inspecting one individual pair of leader-follower trajectories. As for C-C, MAREs in calibration process are 5.63%, 8.70%, 9.09% and 6.58% respectively for VIM, OVM, IDM and DVA, and as for C-T, these values are 6.10%, 7.04%, 6.77% and 13.39% respectively (See figure 5 for visual demonstration). Obviously, when comprehensively comparing these calibration results at the level of single trajectory pair it is easily known that the predicting performance of VIM is more superior than that of other three reference models.

Therefore, above evaluation results at the levels of vehicle type and single trajectory pair show the superiority of VIM in reproducing the trajectory of the following vehicle to other three models for both C-C and C-T. In summary, VIM can better describe the heterogeneous driving behaviors influenced by the leader's vehicle type.



(a) (b)

FIGURE 5 Gap distance fluctuation reproduced by different models.
(a) C-C, (b) C-T.

CONCLUSIONS

This paper proposes a visual imaging model (VIM) to describe the heterogeneous car-following dynamics among different vehicle types. Most traditional car following models (e.g. OVM and IDM) assumed that drivers are perfectly rational and can perceive the 3-D traffic information accurately. On the other hand, those models also do not include parameters that are dependent on vehicle types, which is a critical to model the heterogeneous driving behaviors. Existing visual angle based models only utilizes the 2-D visual angle extent of the leading vehicle or its changing rate as the visual stimulation, which can not describe the whole visual stimulus subtended by the preceding vehicle. The proposed VIM can overcome those shortcomings with the visual imaging size of the leading vehicle and its change rate treated as the stimuli to the follower. Moreover, VIM is also suitable for describing the heterogeneous driving behaviors by adjusting the parameters L_S according to the leader's vehicle type. The model also ensures that under the small gap distance, the larger back size of the leading vehicle can cause stronger stimulus to the follower that result in the greater acceleration or deceleration, but when the gap distance is relatively large, the follower is not sensitive to the back size of the preceding vehicle, which is consistent with the empirical driving experience.

The model is further evaluated by conducting calibration at the level of single trajectory pair and implementing the calibration and validation at the vehicle type level. At the level of single trajectory pair, calibrated VIM is able to reproduce the results of averaged MGDs found in statistical analysis about the US101 NGSIM data, which is that the average MGD for C-C is larger than that for C-T at low velocity range but smaller than that for C-T at high velocity range. At the level of vehicle type, the calibration and validation results by the model are compared with those by other three reference models and favorable conclusions for the model are obtained, which show that the calibrated VIM has more predicting performance in car following dynamics than those three reference models under heterogeneous leader-follower compositions (i.e. C-C and C-T) because of the vehicle type related parameter incorporated in the proposed VIM.

Further research about other kinds of heterogeneity in car following behaviors will be conducted with VIM from the field data, such as various driving styles related to their own different vehicle types and different driving styles within the group of the same vehicle type. Meanwhile, the proposed model has the potential to be extended to more comprehensive and realistic 3-D microscopic simulation models to account for full information on the road (e.g. the 3-D size and shape of the surrounding vehicles, road side objects, curvatures) that can affect microscopic driver behavior.

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APPENDIX A

Optimal Velocity Model (OVM)

Optimal Velocity Model (OVM) was firstly proposed by Bando et al.(*12*) and formulated as

$$a_n(t) = \alpha \left\{ V[\Delta x_n(t)] - v_n(t) \right\}$$

where $a_n(t)$ is the acceleration of vehicle *n* at time *t*, $V[\Delta x_n(t)]$ is the optimal velocity depending on the distance headway, $\Delta x_n(t)$ and $v_n(t)$ are respectively the distance headway and velocity of vehicle *n* at time *t*, α is the sensitivity coefficient. Besides, the selected OV function is written as $V[\Delta x_n(t)] = V_1 + V_2 \tanh\{C_1[\Delta x_n(t) - l_n] - C_2\}$, where l_n is the length of vehicle *n*, V_1, V_2, C_1 and C_2 are four main parameters in the OV function (*29*).

Intelligent Driver Model (IDM)

Treiber et al. (*30*) proposed Intelligent Driver Model (IDM)and defined it by the following acceleration function

$$\dot{v}_{IDM} = a\left\{1 - \left(\frac{v}{v_0}\right)^{\delta} - \left[\frac{s^*(v,\Delta v)}{s}\right]^2\right\}, \text{ where } s^*(v,\Delta v) = s_0 + T \cdot v + \frac{v \cdot \Delta v}{2\sqrt{ab}}.$$

where v_0 is the desired velocity, v is the current velocity, a is the maximum acceleration, δ is the acceleration component, s is the current gap distance, s_0 is the minimum distance in congested traffic, T is the safe time gap for following the leading vehicle, b is the maximum desired deceleration and Δv is the velocity difference between the leader and the follower.

Visual Angle Model (DVA)

Andersen et al.(*18*) presented Driving by Visual Angle Model (DVA) to replace the 3-Dinformation with the optical information, which is formulated as

$$a_{DVA} = j \cdot (\frac{1}{\alpha} - \frac{1}{\alpha^*}) + k \cdot \frac{d}{dt}\alpha$$

where $j > 0$ and $k < 0$ are constants, α and α^* are respectively the current and desired visual angle extent of the leading vehicle, $d\alpha/dt$ is the change rate of α . Moreover, α and α^* canbe expressed as

$$\alpha = \frac{w}{D(t)} \text{and} \, \alpha^* = 2 \cdot a\tan(\frac{w}{t_d \cdot v_f}) .$$

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