Does the Intelligent Driver Model Adequately Represent Human Drivers?

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Abstract: The Intelligent Driver Model (IDM) is one of the widely used car-following models to represent human drivers in mixed traffic simulations. However, the standard IDM performs too well in energy efficiency and comfort (acceleration) compared with real-world human drivers. In addition, many studies assessed the performance of automated vehicles interacting with human-driven vehicles (HVs) in mixed traffic where IDM serves as HVs based on the assumption that the IDM represents an intelligent human driver that performs not better than automated vehicles (AVs). When a commercially available control system of AVs, Adaptive Cruise Control (ACC), is compared with the standard IDM, it is found that the standard IDM generally outperforms ACC in fuel efficiency and comfort, which is not logical in an evaluation of any advanced control logic with mixed traffic. To ensure the IDM reasonably mimics human drivers, a dynamic safe time headway concept is proposed and evaluated. A real-world NGSIM data set is utilized as the human drivers for simulation-based comparisons. The results indicate that the performance of the IDM with dynamic time headway is much closer to human drivers and worse than the ACC system as expected.

1 INTRODUCTION

A human driver model is a key component in representing driver characteristics in microscopic traffic simulations. This is because the assessment of vehicle safety, energy efficiency, and traffic characteristics is highly associated with the reliability of the human driver models. Generally, the car-following model of human drivers estimates the velocity/acceleration according to the velocity/acceleration of its preceding vehicle, and the driver characteristics is represented by standard parameters or calibrated parameters based on real-world data. The commonly used car-following models are Gazis-Herman-Rothery (GHR) model (Gazis et al., 1959), Optimal Vehicle Model (OVM) (Bando et al., 1995) and Intelligent Driver Model (IDM) (Treiber et al., 2000). These models can effectively capture drivers' basic behaviors without requiring much load on the mathematical framework. Due to the collision-free characteristics and mathematical efficiency of the IDM, many studies have employed the IDM to represent the car-following behaviors of human drivers in microscopic traffic simulation, especially mixed traffic simulation. To utilize the IDM as human drivers, the IDM is supposed to describe the microscopic dynamics of the individual drivers as well as macroscopic aspects of traffic flow. However, the complexity and uncertainty of human drivers present a great challenge for IDM to capture their characteristics.

The logic behind the IDM is to model the reactions of a human driver to his/her preceding vehicle's motions (e.g., speed and distance) corresponding to the desire to achieve the desired speed, meanwhile, keeping a safe gap from the preceding vehicle and collision precaution of human drivers in reality. The characteristics of drivers are defined by parameters, e.g., maximum acceleration/deceleration, desired speed, safe time headway, and minimum gap, which can be calibrated with empirical data or real-world data. Many studies (Jiang et al., 2017; Bhattacharyya et al., 2020; Sharma et al., 2021; Mu et al., 2022) employ the IDM modeling homogeneous or heterogeneous human drivers to evaluate the microscopic or macroscopic characteristics of automated vehicles (AVs) in the mixed traffic environment, e.g., fuel efficiency, driving comfort, traffic capacity and stability. Generally, the IDM is utilized to model traditional human-driven vehicles interacting with connected automated vehicles and connected human-

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driven vehicles. In terms of the interaction with automated vehicles in traffic, (Rahman and Abdel-Aty, 2018; Wang et al., 2019; Sun et al., 2020; Guo and Jia, 2021; Ding et al., 2022) evaluated the performance of traffic to show the impact of penetration of connected automated vehicles (CAVs) in energy efficiency in mixed traffic. The IDM parameters refer to the calibrated parameters of real-world human drivers. For interactions with connected human-driven vehicles, (Rahman and Abdel-Aty, 2018; Sharma et al., 2019; Jiang et al., 2019; Zhang et al., 2020) evaluated the safety and mobility of connected vehicles in mixed traffic with connected human-driven vehicles. The IDM was used to represent human driving behaviors of connected vehicles, which can receive other connected vehicles' motion information. However, the limitation of these studies is that neither of them evaluated or compared the performance of each control mode under the mixed traffic of human drivers and automated vehicles. Even though the capability of IDM to represent the stochastic human drivers' car-following is not the focus of their research, it is important for researchers to use a model that can represent the human drivers for reliable assessment.

The most common method of employing IDM serving as human drivers is calibrating parameters with real-world human-driven vehicle data. Various calibration methods have been investigated, e.g., least squared errors or maximum likelihood, to find the range or the distribution of these parameters to simulate different drivers' characteristics (Kesting and Treiber, 2008; Stern, ; Ro et al., 2018; Hegde et al., 2021). However, these studies focus on identifying the most fitting parameters in a long time driving and do not consider that each driver's characteristics could change over time. To overcome these limitations, online estimation methods are utilized to capture the dynamics of individual drivers by utilizing real-time information to update those model parameters. (Bhattacharyya et al., 2020). However, the online estimation method is more about an estimation of human driver behaviors online instead of modeling human driver behaviors in traffic simulation, considering the estimated parameters cannot be used to regenerate human behaviors for new simulations since the estimated parameters are highly associated with the preceding vehicles' behaviors, which could change in different simulations.

To improve IDM model applications, many researchers (Bhattacharyya et al., 2020; Kesting et al., 2010; Eggert et al., 2015; Yi et al., 2020) seek to incorporate realistic human driver features. The Enhanced IDM (Kesting et al., 2010) presents an improved IDM application for safety by preventing the model from over-reactions even when the driver of the preceding vehicle suddenly brakes with the maximum possible deceleration. The Foresighted Driver Model (FDM) (Eggert et al., 2015) extends the IDM by assuming that a driver balances the risk of possible collisions with travel time and the smoothness of the ride. The models mentioned above focus on improving the utilization of the IDM considering safety when human drivers control the vehicles, while the limitations are also their emphasis on the safety of IDM aiming at generating smooth acceleration. However, those models neglect the fact that human drivers actually could have aggressive behaviors. It is apparent that few research investigated the uncertainties of IDM parameters and their impacts on human driving behaviors.

The objective of this research is to assess whether the IDM adequately represents human driving behaviors. To achieve this objective, the performance between the IDM with calibrated parameters and real-world human drivers is to be compared. In addition, since ACC is one of the most commonly used automated control for AVs, which should have better driving comfort and fuel economy than IDM for human drivers, the calibrated IDM is to be compared with the ACC system. If the IDM does not represent human driving behaviors, this research is to conduct experimental design-based evaluations to identify key parameters affecting the performance of the IDM and explore the feasibility of adjusting IDM parameters to adequately represent human driving behaviors. The rest of the paper is organized as follows. Section 2 presents the car following models, including the IDM and ACC, and how they are to be implemented in this paper. Section 3 discussed the real-world human driving data and the efforts given to calibrate the IDM and the comparison results among the human drivers, IDM and ACC. In section 4, the impacts of the IDM parameters are evaluated through an experimental design covering all IDM parameters, an attempt is made to choose an IDM parameter that can best represent human driving behaviors, and the proposed IDM model is validated using a NGSIM data that is not used in the calibration. Finally, section 5 summarizes the findings of this research and discusses future research.

2 CAR-FOLLOWING MODELS

2.1 Intelligent Driver Model

The standard Intelligent Driver Model (IDM) is a deterministic car-following model that describes the dynamics of a human-driven subject vehicle by estimating its acceleration with respect to its speed, speed difference, and the gap from the vehicle ahead. The speed difference introduces additional caution to make IDM crash-free. Five parameters, including safe time headway, desired speed, maximum acceleration, maximum deceleration, and minimum distance, represent the car-following characteristic of the driver, which can be calibrated with empirical or real-world data. The estimated acceleration of the subject vehicle is calculated by Eq. (1) and Eq. (2).

$$a_s(t) = a\left[1-(\frac{v_s(t)}{v_d})^4-(\frac{\triangle\, d_{s,d}(v_s,\triangle\, v_s,t)}{\triangle\, d_s(t)})^2\right] \quad (1)$$

$$\triangle\, d_{s,d} = s_0 + max\left(v_s(t)*T+\frac{v_s(t)\cdot\triangle\, v_s(t)}{2\sqrt{ab}},0\right) \quad (2)$$

Where $\triangle\, d_s(t) = d_p(t) - d_s(t)$ is the gap between the subject vehicle's (s) and its preceding vehicle (p) at time t. $\triangle\, v_s(t) = v_p(t) - v_s(t)$ is the relative speed difference of the subject vehicle and its preceding vehicle at time t. $d_s(t)$, $v_s(t)$, $a_s(t)$ are the states representing the position, speed, and acceleration of the subject vehicle at time t, respectively. $\triangle\, d_{s,d}$ is the desired bumper to bumper gap and $\triangle\, d_s(t)$ is the actual bumper to bumper gap at time t. The five parameters are interpreted as follows. v_d is the desired speed of the driver driving in free flow. a is the maximum acceleration. b represents a comfortable deceleration. s_0 is the minimum inter-vehicle gap that the driver prefers to maintain at the stop. T is the safe time headway.

2.2 Adaptive Cruise Control

Adaptive Cruise Control (ACC) (Vahidi and Eskandarian, 2003) is a commercially available advanced driver assistance system of longitudinal control that is designed for autonomous vehicles and aims at improving safety, driving comfort, energy economy, and traffic flow(Marsden et al., 2001). The ACC systems utilize the measured motion of the preceding vehicle and control the subject vehicle to maintain a safe gap. A proportional-derivative (PD) controller is utilized for the ACC systems in this study. The control input $u_e(t)$ can be written with respect to the spacing error $e(t)$:

$$u(t) = k_p e(t) + k_d \dot{e}(t) \quad (3)$$

where k_p, and k_d are proportional and derivative gains of the controller, respectively. The spacing error $e(t) = d_s(t) - d_p(t)$ is the difference between the desired gap of the subject vehicle from the immediately preceding vehicle d_p and the actual gap $d(t)$ at time t. The desired gap $d_d(t) = v_s(t)\cdot T_s + d_0$ is calculated by the desired time headway T_s, current speed v_s and standstill distance d_0. The low-level controller is modeled by a first-order lag τ to the acceleration command $u(t)$ and vehicle acceleration $a(t)$:

$$\dot{a}(t) = -\frac{a(t)}{\tau} + \frac{u(t)}{\tau} \quad (4)$$

In this study, we adopted system parameters, $k_p = 0.7, k_d = 0.5$, and $\tau = 0.3$.

3 HUMAN DRIVERS DATA AND IDM CALIBRATION ISSUE

3.1 NGSIM Dataset and Pre-Processing

To understand microscopic car following behaviors of human drivers, the freeway US-101 data set from the Next Generation Simulation (NGSIM) (Administration, 2017) was utilized. The data set consists of about 2000 vehicles' trajectories on five lanes observed within a short distance (roughly 640 m) and for the first 15 minutes of the dataset, and it reflects dense highway flow, the transition between uncongested and congested conditions, as well as full congestion. In this study, we only utilized the data from uncongested conditions to analyze car-following behaviors.

This NGSIM trajectory data includes the position and speed profile of vehicles at a 0.1-second time interval. Due to the propagation of the measurement error in the speed profiles, considerable noise (i.e., unrealistic jerks) in acceleration could be generated when derived from the speed profiles of vehicles. Therefore, in this study, the locally weighted scatterplot smoothing (LOWESS) is applied to the speed profiles of vehicles, and the size of the sliding window is chosen as 2s. After smoothing, the speed profiles of vehicles are less noisy, and the jerks are always below $15m/s^3$, which is more mechanically realistic (Punzo et al., 2011).

3.2 Intelligent Driver Model Calibration Issue

Several IDM calibration methods (Chen et al., 2010; Ciuffo et al., 2014; Bhattacharyya et al., 2020; Alhariqi et al., 2022) to estimate the IDM parameters were used in many studies where the parameter estimation employed optimization techniques to minimize the error between the simulated and measured output. Most studies focused on finding the constant parameters of IDM to minimize the speed and gap errors from human drivers. One limitation is that most studies showed the error or how much improvement the error is with the proposed method. In contrast, limited studies show the actual performance comparison of human drivers and IDM. Besides, the complexity and uncertainty of human drivers' characteristics are neglected. To make a fair comparison with other studies, the cost function which is the sum of the square error of the simulated speed profiles and time headway profiles of IDM from that of the actual human drivers is minimized during the IDM parameters estimation.

The cost function which is related to the simulated speed v_{sim}, actual speed from data v_{data}, the simulated time headway T_{sim}, actual time headway from data T_{data}, is defined in Eq.5

$$\begin{aligned} f(v_{sim}, T_{sim}) = \sum_{t=0}^{t_n} [& (v_{sim}(t) - v_{data}(t))^2 \\ & + (T_{sim}(t) - T_{data}(t))^2] \end{aligned} \tag{5}$$

$$\begin{aligned} \min_{v_{sim}, T_{sim}} \quad & f(v_{sim}, T_{sim}) \\ \text{s.t.} \quad & T_{min} \leq T \leq T_{max} \\ & v_{dmin} \leq v_d \leq v_{dmax} \\ & s_{0min} \leq s_0 \leq s_{0max} \\ & a_{min} \leq a \leq a_{max} \\ & b_{min} \leq b \leq b_{max} \end{aligned} \tag{6}$$

Each parameter of the IDM is constrained by its maximum value and minimum value. The safe time headway, T, is in range of (0.8, 2) m; the desired speed, v_d, is in range of (20, 28) m/s; the maximum acceleration/deceleration, a/b, is in range of (1, 5) m/s^2, and the minimum distance, s_0, is within (1, 5) m. The optimization problem, Eqs. 5 and 6, is solved by applying a trust-region reflective least squares algorithm with constraints (Coleman and Li, 1996). The algorithm is simple yet powerful and specially designed to solve nonlinear equations and is efficient for nonconvex problems with constraints.

Twenty pairs of human car-following trajectories from the NGSIM data set were selected and utilized as the preceding vehicles of the subject vehicles modeled by IDM and evaluated in terms of acceleration

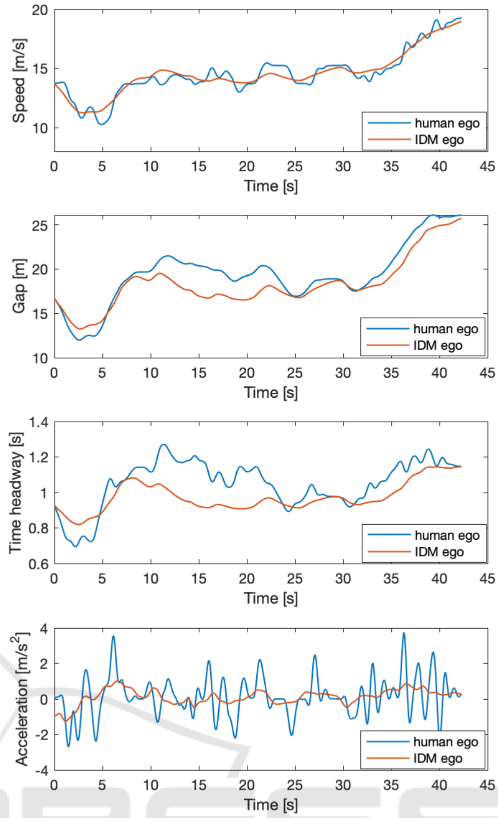

Figure 1: Comparison of speed, gap, time headway and acceleration between real-world human drivers and IDM.

and fuel consumption performance. It is noted that the safe time headway of IDM and ACC are set as the same for fair comparisons. Seven metrics, speed mean, speed standard deviation (Std), gap mean, gap Std, acceleration (Accl.) mean, acceleration Std and fuel consumption that is estimated by Virginia-Tech fuel consumption model(Rakha et al., 2011) are evaluated for performance comparisons.

Table 1 shows the IDM performance with calibrated parameters and comparisons to real-world human drivers and the ACC systems. The calibrated parameters are shown in Table 2. From Table 1, it could be seen that the speed and gap of the IDM are similar to those of human drivers, while the acceleration and fuel consumption of the IDM have a significant difference to real-world human drivers, as shown in Figure

Table 1: Performance comparison of human drivers, calibrated IDM, and ACC.

Model	Speed Mean $[m/s]$	Speed. Std	Gap Mean $[m]$	Gap. Std	Accl. Mean $[m/s^2]$	Accl. Std	Fuel $[ml]$	Fuel Std
Human Drivers	12.95	2.97	22.37	5.34	0.76	1.07	64.92	7.92
IDM	12.91	2.75	21.73	5.17	0.42	0.49	45.42	7.32
ACC	12.96	2.90	20.07	4.25	0.47	0.55	48.64	7.72

1. More importantly, the IDM performs even better than the ACC systems, which is unlikely and makes the IDM not suitable to serve as a human driver model in mixed traffic, including automated control systems.

Table 2: Calibrated parameters of IDM (20 pairs).

Parameter Name (Unit)	Mean	Std
Safe time headway (T, s)	1.12	0.34
Maximum acceleration $(a_{max}, m/s^2)$	2.45	1.30
Maximum deceleration $(b_{max}, m/s^2)$	4.28	1.17
Desired speed $(v_d, m/s)$	24.89	2.02
Minimum distance (s_0, m)	2.23	1.32

4 IMPACT ASSESSMENT OF IDM PARAMETERS

4.1 Identifying Key IDM Parameters

In this study, an analysis using the Monte Carlo technique is implemented to assess how the parameters and states of the IDM influence the optimization cost function. This approach uses a representative set of samples to explore the design space. The five parameters of the IDM, safe time headway T, maximum acceleration a_{max} and deceleration b_{max}, and desired speed v_d and minimum distance s_0 are evaluated for 20 pairs of trajectories from NGSIM data, and their ranges are set as (0.8, 2) s , (1, 5) m/s^2 , (1, 5) m/s^2, (20, 26) m/s and (1, 5) m respectively. The distribution of randomly generated parameters is assumed to be a uniform distribution. The reason why the uniform distribution is set is that the restricted interval is small so that any value within such range is equally likely. 1000 samples for each parameter from the following distribution are generated for analysis.

The design requirements for this analysis are to match the IDM's time headway and speed trajectories with those of real-world human drivers. As the relationship between five parameters and the cost function is complex, three different statistical analysis, Rank correlation(Rutherford, 2005), Kendall correlation (Kendall and Gibbons, 1990), and Rank standardized Regression (Greenland et al., 1991) are conducted to analyze the impacts of parameters from IDM. The rank correlation, referred to as Spearman analysis, is to measure the degree of similarity between two variable rankings based on the assumption that a nonlinear monotonic relation between the parameters and the cost function. The Kendall correlation measures the ordinal association between two measurements and it does not rely on any assumptions about the distributions. Rank standardized Regression usually evaluates which of the independent variables has a more significant effect on the dependent variable in a multiple regression analysis based on the assumption that the parameters could linearly influence the cost function.

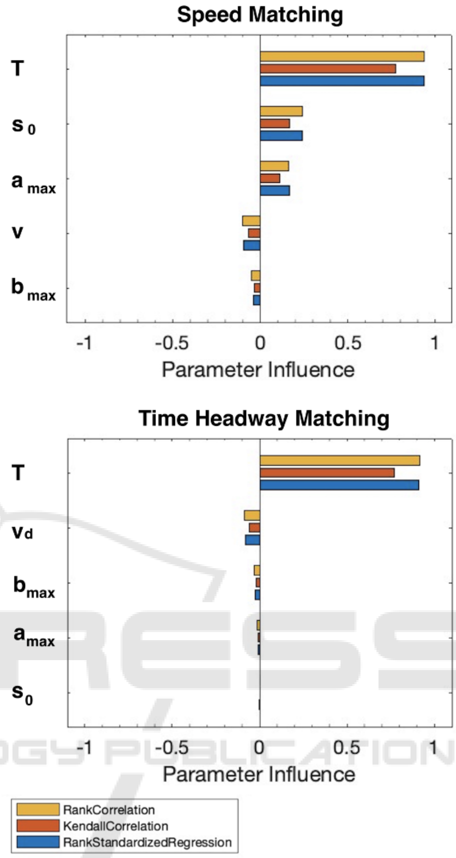

Figure 2: Sensitivity Analysis Results.

The statistical results are shown in Figure 2 where the first figure shows the influence to the speed matching and the second figure shows the influence to the time headway matching. From Figure 2, it could be seen that the safe time headway parameter is the most influential parameter of the IDM to mimic human drivers' time headway and speed trajectories for all three statistical tests. For the other four parameters, it has different influential ranking to the speed and time headway. The minimum distance s_0 ranks as the second influential parameter for speed trajectory, while it is the least influential parameter for time headway. On the contrary, the desired speed v_d is the second influential parameter for time headway, while it is the second least influential parameter for speed. It is noted that apart from safe time headway, the other four parameters' correlation value is less than 0.3, which means that compared to the safe time headway which plays the most significant role in the IDM to mimic human drivers' car-following behaviors, the influence of other four parameters is limited.

4.2 Time Headway of the IDM and Human Drivers

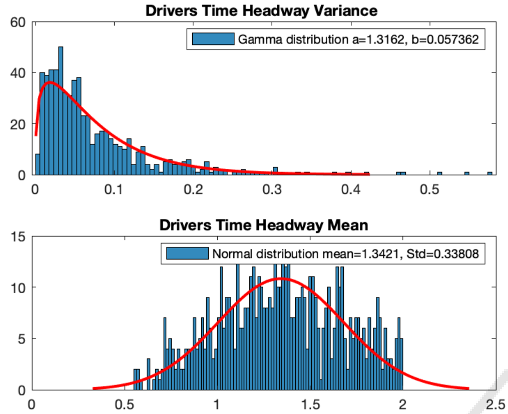

Figure 3: The calibrated distribution of the variance and mean of time headway for human drivers.

As the safe time headway is identified as the most influential parameter in the IDM model, we further investigated the time headway trajectory of real-world human drivers and compared it with that of the IDM generated. Human drivers with an average time headway within 2 seconds (533 pairs) are extracted from NGSIM data for evaluations and comparisons. To observe the time headway of human drivers, the mean and variance of time headway profiles of 533 human drivers are calculated and shown in Figure 3. In addition, the change of time headway also needs to be investigated for analyzing the stochastic human driver behaviors. The time headway and time headway change $\triangle T(t) = T(t + \triangle t) - T(t)$ for each time step (0.1 seconds) are also shown in Figure 4.

From Figure 3, it could be seen that human drivers have different characteristics. The safe time headway of different human drivers have a wide range of mean and variance, while the time headway changes of most human drivers are within [-0.1, 0.1] seconds. From these observations, the human drivers tend to have more fluctuating time headway than that the IDM generates. An example of a comparison between real-world human drivers and the calibrated IDM is shown in Figure 1. From Figure 1, it could be seen that IDM generated a more stable time headway than human drivers. This is mainly attributed to the constant time headway setting. The IDM was able to reach the desired time headway and maintain it steadily to follow the preceding vehicle, while human

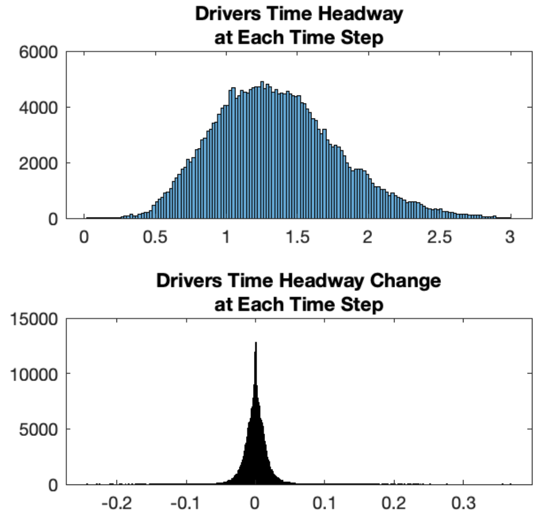

Figure 4: Histograms of drivers' time headway and their time headway change at each time step (533 pairs).

drivers were not. Therefore, constant time headway is one reason that limits the IDM's capability to mimic human driver behaviors.

4.3 Calibration Performance Comparison

Based on the conclusion from the previous section, instead of using the constant safe time headway T in the IDM, a dynamic time headway, $T(t)$, is proposed for IDM to mimic human driver behaviors (IDM-T_t). To utilize dynamic time headway and evaluate the impacts to the IDM, the data of human drivers were analyzed. Based on the time headway at each step shown in Figure 4, the dynamic time headway is assumed to follow a normal distribution, and the variance and mean are generated for each human driver's characteristics. To exclude unrealistic time headway changes in the simulation, the time headway change is constrained within [-0.1, 0.1] seconds based on Figure 4. The rest of the parameters of the IDM with dynamic time headway shown in Figure 4 are the same as the parameters of the standard IDM which are calibrated using the optimization method mentioned in Section 3.2.

The performances of the standard IDM, IDM with dynamic time headway, ACC, and human drivers are shown in Table 3. From Table 3, it could be seen that the standard IDM performed similarly to ACC in acceleration but had better fuel consumption than ACC. When the IDM is compared with human drivers, it performs significantly better in acceleration and fuel consumption. This means that the IDM cannot adequately represent human drivers in terms of comfort

Table 3: Performance Comparison of IDM, IDM-T_t, ACC, human drivers.

Model	Speed Mean $[m/s]$	Speed. Std	Gap Mean $[m]$	Gap. Std	Accl. Mean $[m/s^2]$	Accl. Std	Fuel $[ml]$	Fuel Std
Human Drivers	12.62	2.72	21.10	4.71	0.78	1.12	60.45	10.43
IDM-T_t	12.63	2.53	20.17	4.12	0.90	1.11	61.42	10.92
IDM	12.59	2.54	20.92	4.79	0.38	0.47	38.84	9.12
ACC	12.6	2.66	18.30	3.73	0.43	0.52	41.47	9.73

Table 4: Calibrated parameters of IDM (533 pairs).

Parameter Name (Unit)	Mean	Std
Safe time headway (T, s)	1.14	0.34
Maximum acceleration $(a_{max}, m/s^2)$	2.19	1.25
Maximum deceleration $(b_{max}, m/s^2)$	4.25	1.20
Desired speed $(v_d, m/s)$	24.48	2.25
Minimum distance (s_0, m)	2.18	0.96

and fuel efficiency. If the IDM were used in a microscopic simulation to represent human drivers, it is unlikely to accurately estimate the improvement from ACC or other control systems of automated vehicles. However, with dynamic time headway, the IDM-T_t performed more similarly to that of human drivers compared with IDM, which could be seen from Table 3. Based on the t-test, the fuel efficiency and acceleration of the IDM with dynamic time headway (IDM-T_t) is not significantly different from human drivers. The IDM with constant time headway and ACC systems are significantly different from human drivers in all metrics.

4.4 Validation Performance Comparison

This subsection performed the validation of the calibrated IDM-T_t using the NGSIM human drivers' trajectory data that were not used during the calibration. This is necessary to ensure the calibrated IDM with dynamic headway is applicable to general human driven vehicles. A total of 100 pairs of human drivers' trajectories were used. To validate the proposed dynamic time headway in the IDM-T_t, the calibrated time headway and other parameters are implemted using different trajectories in the NGSIM data set and compared with those of human driven vehicles. The parameter settings shown in Figure 4 are analyzed to create a probability distribution for the variance of the safe time headway by fitting an appropriate distribution. The distribution is identified as shown in Figure 3. The variance of the time headway follows a Gamma distribution with $a = 1.32, b = 0.057$. The mean value of the time headway follows a normal distribution with a mean of 1.34 and a standard deviation of 0.34 and the value generated by this distribution is constrained within [0.8, 2] s.

Based on the calibrated distribution of time headway and the calibrated parameters in Table 4, the IDM, IDM-T_t, and ACC were simulated and compared with human drivers shown in Table 5. The simulation process is the same with the previous section. From Table 5, it could be seen that the IDM-T_t was not able to perform as well as the calibrated results, while IDM-T_t still performed more similar to human drivers compared with the standard IDM.

5 CONCLUSIONS AND FUTURE WORK

In this study, we investigated the limitations and potential of IDM to represent human drivers for microscopic traffic simulation. To evaluate the reliability of IDM to represent human drivers, the calibrated IDM is compared with real-world human drivers and the ACC system. The parameters of the IDM were calibrated in terms of speed and time headway matching to human drivers based on real-world NGSIM data set. The simulation results showed that the IDM matches well with the speed and gap of human drivers, while it performs significantly better than human drivers and ACC systems in comfort and fuel efficiency, which makes it inadequate to represent human drivers. Therefore, in order to improve IDM application for human drivers, the safe time headway, which is the most influential parameter in the IDM, was proposed to be dynamic instead of using a constant static value. To evaluate the impacts of the dynamic time headway to IDM application on human drivers, 633 pairs of car-following behaviors of human drivers from the NGSIM data set were compared with IDM, IDM with dynamic time headway, and ACC control mode with calibration and validation. With dynamic time headway, IDM can be more similar to human drivers than the standard IDM in fuel consumption based on the paired t-test and have a significant improvement in acceleration similarity. It is expected that the proposed dynamic safe headway-

Table 5: Validation Performance of IDM, IDM-T_t, ACC and human drivers.

Model	Speed Mean $[m/s]$	Speed. Std	Gap Mean $[m]$	Gap. Std	Accl. Mean $[m/s^2]$	Accl. Std	Fuel $[ml]$	Fuel Std
Human Drivers	12.52	1.85	20.25	3.32	0.92	1.24	44.54	14.97
IDM-T_t	12.52	1.64	19.41	2.66	0.84	1.03	39.11	14.84
IDM	12.46	1.63	20.32	3.28	0.36	0.42	24.55	9.97
ACC	12.48	1.73	14.82	2.39	0.43	0.52	26.67	11.58

based IDM improves the evaluation of mixed traffic interacting with human-driven vehicles and connected automated vehicles (Chen and Park, 2020).

In this study, safe time headway is the only parameter we adjusted to represent human drivers. While the other parameters in the IDM were less influential, they should be considered to be adjusted for more accurate human driver modeling. The dynamic time headway is based on the normal distribution and the change is constrained based on real-world data. However, the value and the direction of time headway change have not been well-investigated, which will be investigated in future research. Besides, vehicle stop and vehicle catch-up behaviors are not considered in this study. Given these behaviors are also essential to human driver behavior modeling in microscopic simulation, these behaviors should be investigated for human driver modeling.

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