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Research Article

Research on Car-Following Model considering Driving Style

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In this paper, a car-following model considering various driving styles is constructed to fulfill the personalized needs of different users of autonomous vehicles. First, according to a set of selection rules, car-following events are selected from the Next Generation Simulation (NGSIM) dataset, and then through an unsupervised machine learning method, the extracted data are divided into two styles, i.e., conservative and aggressive. Statistical analysis is then conducted to analyze the differences in vehicle speed, acceleration, desired time headway, and so on between both driving styles. Based on the analysis, a car-following model based on model predictive control is designed. Experimental results from testing data show that the proposed car-following models demonstrate different driving styles in terms of safety, comfort, and effectiveness. The conservative driving model is safer and more comfortable than the radical driving model, but the driving efficiency is low.

1. Introduction

A car-following model is one of the most important microscopic traffic flow models [1] and depicts the longitudinal behavior of a vehicle and its interaction with leading vehicle(s) in the same lane [2]. Controlling vehicle velocity to maintain a safe and comfortable following distance is the main goal of a car-following model [3]. The first car-following model was developed in the 1950s [4], and a large number of traditional car-following models have been proposed since then [5], e.g., the intelligent driver model (IDM) [6], Gazis–Herman–Rothery (GHR) model [7], optimal velocity model [8], and Wiedemann model [9]. In addition, many car-following models based on intelligent algorithms and machine learning have been developed in recent years. Luo et al. [10] proposed a car-following model based on a model-predictive-control (MPC) framework with multiple objectives. Zheng et al. [11] presented a car-following model with a k-nearest-neighbor algorithm, which outputs the most similar cases with the trained model. Jia et al. [12] introduced a method to model car-following behavior with an artificial neural network, which takes several inputs and uses them to predict acceleration. Zhu et al. [3] proposed a model based on reinforcement learning that, through training, can effectively control the speed during car following.

Since the individual perception of comfort is different, it is not enough to simply study the car-following model. Some studies have aimed to meet the personalized needs of different users and focused on car-following models in which driving styles are considered. For example, Lefevre et al. [13] presented a car-following model based on a non-parametric regression method, which is a combination of a hidden Markov model (HMM) and Gaussian mixture regression (GMR). The function of the Lefevre et al. model is to produce an acceleration sequence using historical data. However, this approach does not address the generation issue of the model since the model is employed to compute an acceleration sequence online that would only replicate what a human driver would do in the corresponding circumstances. For general scenarios, the performance of the model must be further studied. Kuderer et al. [14] proposed an inverse reinforcement learning method to learn driving styles from demonstrations. In this situation, the expected feature values of the model are matched with observed empirical feature values. Experimental results suggested that the method can learn distinct policies for different users. The limitation of this study is that the speed-change range is limited to the range of 23–29 m/s and is not convincing in other cases. Li et al. [15] modeled the traffic environments and driving styles with an artificial potential field (APF). The APF values are used in the MPC model design process. In this way, people's driving habits and styles are added to the controller. Although this algorithm can reflect driving style, it needs a complex and effective APF design.

A personalized car-following model based on an MPC algorithm, which can effectively solve the multiobjective optimization problem under constraints, is proposed herein. The multiple objectives include minimizing the following: (1) the error between actual inter-vehicle distance and desired inter-vehicle distance to reflect driving styles, (2) the relative speed to the leading vehicle to maintain following behavior, and (3) the acceleration and the jerk to ensure comfort. In addition, constraints can be integrated into the driving style while ensuring safety.

The rest of this paper is structured as follows. In Section 2, the dataset and car-following-event extraction rules are introduced. In Section 3, a k-means clustering algorithm is used to classify driving style, and the classified data are analyzed based on statistical methods. In Section 4, the method of the personalized driver car-following model is discussed. In Section 5, the performance of the proposed model is evaluated through comparative simulation. Finally, our main conclusions and future directions are presented in Section 6.

2. Data Preparation

2.1. Dataset. The Next Generation Simulation (NGSIM) data that were collected in 2005 by the U.S. Federal Highway Administration were used in this work. They provide precise location information for every vehicle, recorded at 10 Hz, resulting in detailed lane positions and locations relative to other vehicles. More specifically, we considered the I-80 dataset retrieved from Interstate 80 in Emeryville, CA, in the San Francisco Bay Area on April 13, 2005. The study area measures approximately 503 m and includes eight lanes: five driving lanes, one on-ramp lane, one off-ramp lane, and one merging lane. The dataset contains 45 min of trajectories for vehicles on I-80, divided into three 15-minute periods: 4:00 p.m.–4:15 p.m., 5:00 p.m.–5:15 p.m., and 5:15 p.m.–5:30 p.m. The trajectory data of the timespan 4:00 p.m.–4:15 p.m. were used in this study.

2.2. Data Preprocessing. Since the NGSIM raw data are acquired from video analysis, they contain many chronic errors and noise [16]. Therefore, the Savitzky–Golay filter [17], using a third-order polynomial with window length 21, was employed to smooth the speed and acceleration data, as illustrated in Figure 1.

2.3. Car-Following-Event Extraction. Car-following models explain the driving states of a following vehicle (FV) responding to the movements of a leading vehicle (LV) [18]. Figure 2 shows a typical car-following scene. In the same lane, the driver of the following vehicle adjusts the driving speed of their own vehicle in real time according to the driving behavior of the leading vehicle to maintain the desired distance; d refers to the inter-vehicle distance between two vehicles.

In line with the above definition of a car-following event, the extraction rules are defined as follows.

(1) The LV and FV stay in the same lane.

(2) Lanes 1–5 are selected. The on-ramp/off-ramp driving state may affect normal car-following behavior.

(3) Only the vehicle type "car" is extracted. Different types of vehicles behave differently when following.

(4) The timespan of the following event is > 15 s, ensuring that car following lasted long enough to be analyzed [3].

According to the above rules, a total of 572 vehicle pairs (259,860 trajectory samples) were collected from the dataset. For extracted car-following events, 70% were used for driving style analysis and determining the design parameters of the models, and 30% were used for testing.

3. Driving Style Cluster Analysis

Driving data that can reflect driving style are needed to build a personalized car-following model. For this purpose, the data must be categorized effectively based on different driving styles.

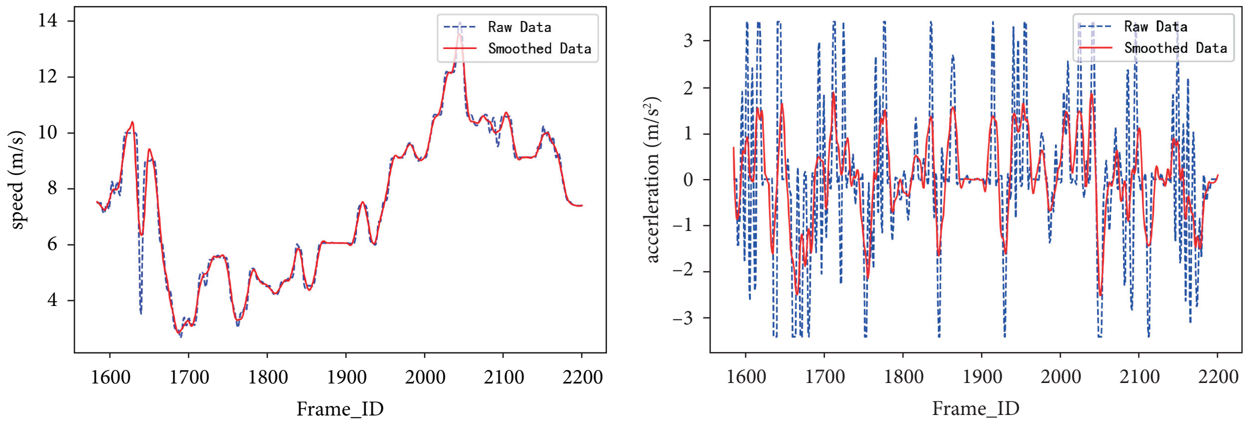
Different behavior characteristics have been used in different studies to identify driving styles. Aljaafreh et al. [19] and Chen and Chen [20] selected acceleration and speed of the FV as characteristics to identify driving style, while Li et al. [15] chose acceleration and time headway. Gao et al. [21] used a group of variables, e.g., relative speed, time headway, and jerk, to reflect the differences in driving styles. Sun et al. [22] utilized inter-vehicle distance, speed, and acceleration/deceleration as car-following variables to analyze driving style.

Combining the inter-vehicle distance and speed of an agent vehicle, the time to collision inverse (TTCi) is defined as follows:

$$\mathrm{TTCi} = \frac{\Delta v}{d}, \tag{1}$$

where Δv is the relative speed between the LV and FV and d is the inter-vehicle distance. In the present work, TTCi, time headway, and the absolute value of acceleration/deceleration were selected as the behavior characteristics to reflect the driving style. Drivers were clustered into two driving styles: conservative and aggressive, by a k-means algorithm [18]. The clustering results are shown in Figure 3, from which it can be seen that aggressive drivers tend to maintain less time headway, less TTCi, and higher acceleration than conservative drivers. The clustering centers are shown in Table 1.

Figure 4 presents the distribution of car-following speed and acceleration at which the different driving styles exhibit



(a) (b)

FIGURE 1: Raw and smoothed NGSIM data using Savitzky–Golay filter for vehicle 515. (a) Longitudinal speed. (b) Longitudinal acceleration.

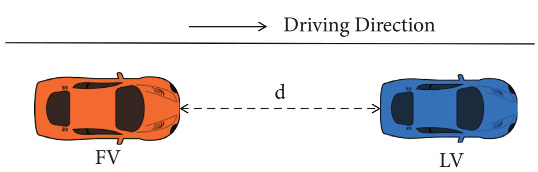


FIGURE 2: Car-following scene.

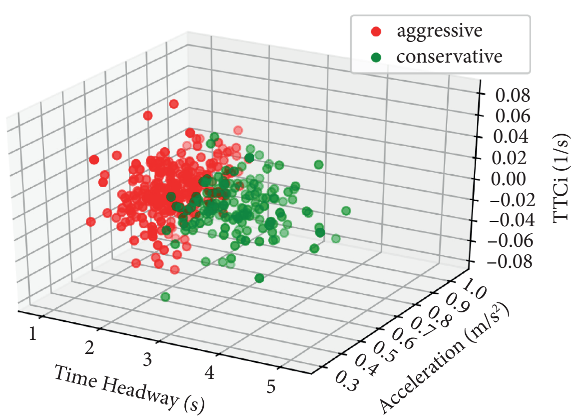


FIGURE 3: Clustering results of k-means algorithm.

a statistically distinct difference. In the conservative driving style, the median value of the speed is approximately 7.18 m/s, the minimum value of the speed is 0.13 m/s, and the maximum value of the speed is 20.18 m/s. In the aggressive driving style, the same values are 9.76, 1.33, and 31.24 m/s, respectively. The acceleration shows no greater difference than speed, but specifically, approximately 99% of the acceleration value distribution ranged from $-3\,\mathrm{m/s^2}$ to $3\,\mathrm{m/s^2}$ for aggressive driving style and from $-2.5\,\mathrm{m/s^2}$ to $2.5\,\mathrm{m/s^2}$ for conservative driving style.

4. Car-Following Model That Considers Driving Style

We obtained different driving styles' trajectory data, and the analysis in the preceding section shows differences between conservative and aggressive drivers. These differences involve time headway, TTCi, speed, and acceleration in car-following behavior. Consequently, these indicators are used to quantify driving styles in modeling.

4.1. Spacing Strategy. Drivers of the same style tend to maintain similar time headway in car-following scenes, but there are great differences in time headway between different styles. In this work, a car-following model is designed based on the method of constant time headway. The equation of the desired inter-vehicle distance is

$$\Delta d_{\mathrm{des}} = v_f t_h + d_0, \tag{2}$$

where v_f is the driving speed of the following vehicle and t_h is the desired time headway; in the conservative driving style, t_h is 3.16 s, and in the aggressive style, it is 1.92 s. d_0 is a safe distance when the vehicle is driving at 0 km/h or very low speed. In this paper, the inter-vehicle distance when the speed is less than 5 km/h (1.39 m/s) is taken as d_0. According to statistics, the value of d_0 is 5.56 m in the conservative driving style but 3.36 m in the aggressive style.

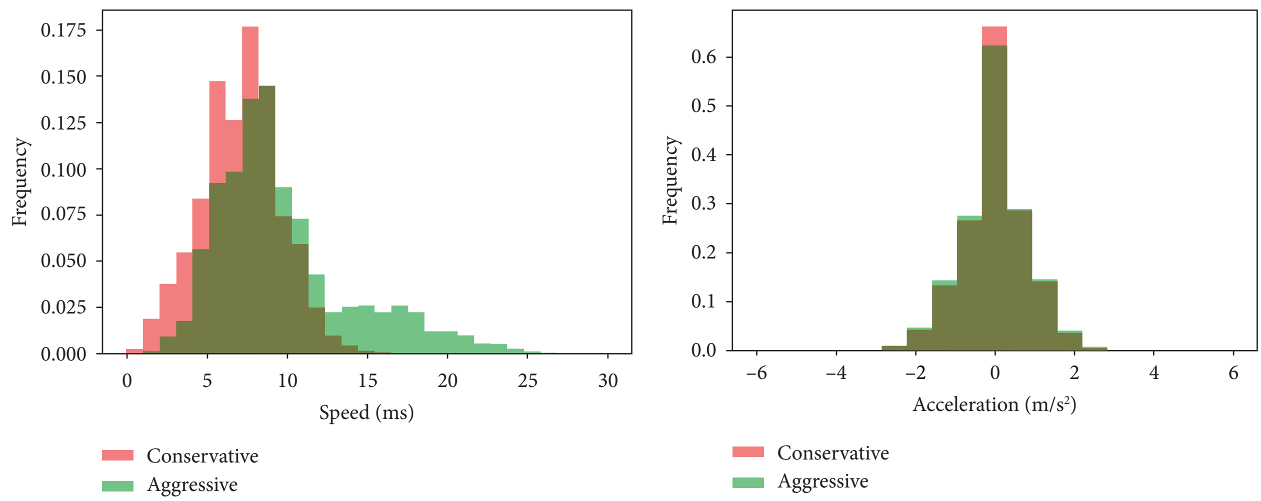
4.2. Car-Following Model. Based on the longitudinal kinematics between the FV and LV, the following equation can be derived:

$$\begin{aligned} \mathbf{x}(k+1) &= \mathbf{A}\mathbf{x}(k) + \mathbf{B}u(k), \\ \mathbf{y}(k) &= \mathbf{C}\mathbf{x}(k), \end{aligned} \tag{3}$$

where

Table 1: Clustering centers of car-following variables for different driving styles.

Driving style	Driver number	Time headway (s)	TTCi (1/s)	Acceleration (m/s^2)
Conservative	136	3.1602	0.0011	0.5982
Aggressive	268	1.9221	−0.0002	0.6399



(a) (b)

Figure 4: Distribution of car-following speed and acceleration. (a) Distribution of speed. (b) Distribution of acceleration.

$$
\begin{aligned}
\mathbf{x}(k) &= [\,\Delta d(k) \;\; \Delta v(k) \;\; v(k)\,]^T,\\
u(k) &= a(k),\\
\mathbf{A} &= \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix},\\
\mathbf{B} &= \begin{bmatrix} -0.5\Delta t^2 \\ -\Delta t \\ \Delta t \end{bmatrix},\\
C &= \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix},
\end{aligned}
\tag{4}
$$

where k represents the kth time point, Δt is the sampling interval (0.1 s), Δd is the inter-vehicle distance between the FV and LV, v is the speed of the FV, and a is the acceleration of the FV.

The target of car following is that the driver adjusts the vehicle's speed to that of the LV and maintains the inter-vehicle distance to the expected value.

Objectives: $\Delta d_{\mathrm{err}}(k) \longrightarrow 0; \Delta v(k) \longrightarrow 0$,where Δd_{err} is the inter-vehicle distance error, defined as follows:

$$\Delta d_{\mathrm{err}} = \Delta d - \Delta d_{\mathrm{des}}. \tag{5}$$

To provide comfort to the passengers during car following, the absolute value of acceleration and jerk must also be as small as possible.

Objectives: $|a(k)| \longrightarrow 0, |j(k)| \longrightarrow 0$,where the jerk is defined as follows:

$$j(k) = \frac{a(k) - a(k-1)}{\Delta t}. \tag{6}$$

In the conservative driving style, the largest value of jerk is defined as

$$\frac{2.5m/s^2 - \left(-2.5m/s^2\right)}{0.1\,s} = 50m/s^2, \tag{7}$$

and in the aggressive driving style, the largest value of jerk is defined as

$$\frac{3m/s^2 - \left(-3m/s^2\right)}{0.1\,s} = 60m/s^2. \tag{8}$$

Constraints must be met when solving optimization problems. First, to avoid collision with the LV, the inter-vehicle distance must satisfy the constraint of the minimum value; here, the minimum value is defined as d_0. Meanwhile, to ensure that FV is in the car-following scene, the distance should be smaller than the maximum car-following distance (45.72 m). Second, the minimum and maximum values of speed, acceleration, and jerk must also be constrained.

Constraint 1: $d_0 \le \Delta d(k) \le d_{\max}$.

Constraint 2: $v_{\min} \le v(k) \le v_{\max}$.

Constraint 3: $a_{\min} \le a(k) \le a_{\max}$.

Constraint 4: $j_{\min} \le j(k) \le j_{\max}$.

The specific values of the above constraints in different styles are shown in Table 2.

Table 2: Constraint values of two driving style models.

Driving style	d_0 (m)	$d_{\max}$ (m)	$v_{\min}$ (m/s)	$v_{\max}$ (m/s)	$a_{\min}$ (m/s^2)	$a_{\max}$ (m/s^2)	$j_{\min}$ (m/s^3)	$j_{\max}$ (m/s^3)
Conservative	5.56	45.72	0.13	20.18	−2.5	2.5	−50	50
Aggressive	3.36	45.72	1.33	31.24	−3.0	3.0	−60	60

4.3. Model Predictive Control. MPC is a form of control in which the current control action is acquired by solving online, and the first value of the fixed control sequence, which is obtained by solving an open-loop optimal control problem [23], is applied. Then, the horizon continues a step and the procedure is repeated. MPC can solve multivariable and constrained problems, so it is suitable to incorporate the car-following model into the MPC framework.

Based on the principles of MPC, the modeling of a car-following problem is calculated as follows:

$$\mathbf{Y}(k) = \mathbf{\Psi}\boldsymbol{\xi}(k) + \mathbf{\Theta}\Delta\mathbf{U}(k), \tag{9}$$

where

$$\begin{aligned}
\mathbf{Y}(k) &= \begin{bmatrix} \boldsymbol{\eta}(k+1|k) \\ \boldsymbol{\eta}(k+2|k) \\ \vdots \\ \boldsymbol{\eta}\left(k+N_p|k\right) \end{bmatrix}, \\
\boldsymbol{\eta}(k+i|k) &= \overline{\mathbf{C}}\boldsymbol{\xi}(k+i|k) i\varepsilon\left[1, N_p\right], \\
\overline{\mathbf{C}} &= [\mathbf{C} \ \ 0], \\
\boldsymbol{\xi}(k+i|k) &= \begin{bmatrix} \mathbf{x}(k+i|k) \\ \mathbf{u}(k+i-1|k) \end{bmatrix}, \\
\mathbf{\Psi} &= \begin{bmatrix} \overline{\mathbf{CA}} \\ \overline{\mathbf{CA}}^2 \\ \vdots \\ \overline{\mathbf{CA}}^{N_p} \end{bmatrix}, \\
\overline{\mathbf{A}} &= \begin{bmatrix} \mathbf{A} & \mathbf{B} \\ 0 & \mathbf{I} \end{bmatrix}, \\
\boldsymbol{\xi}(k) &= \begin{bmatrix} \boldsymbol{\xi}(k+1|k) \\ \boldsymbol{\xi}(k+2|k) \\ \vdots \\ \boldsymbol{\xi}\left(k+N_p|k\right) \end{bmatrix}, \\
\Theta &= \begin{bmatrix} \overline{\mathbf{CB}} & 0 & \cdots & 0 \\ \overline{\mathbf{CAB}} & \overline{\mathbf{CB}} & \cdots & 0 \\ \vdots & \vdots & \vdots & 0 \\ \overline{\mathbf{CA}}^{N_p-1}\overline{\mathbf{B}} & \overline{\mathbf{CA}}^{N_p-2}\overline{\mathbf{B}} & \cdots & \overline{\mathbf{CA}}^{N_p-N_c-1}\overline{\mathbf{B}} \end{bmatrix}, \\
\overline{\mathbf{B}} &= \begin{bmatrix} \mathbf{B} \\ \mathbf{I} \end{bmatrix}, \\
\Delta\mathbf{U}(k) &= \begin{bmatrix} \Delta u(k|k) \\ \Delta u(k+1|k) \\ \vdots \\ \Delta u\left(k+N_c|k\right) \end{bmatrix}, \\
\boldsymbol{\xi}(k+i|k) &= [\mathbf{x}(k+i|k) \ \ u(k+i|k)]^{\mathrm{T}}, \\
\Delta u(k+i|k) &= u(k+i|k) - u(k+i-1|k),
\end{aligned} \tag{10}$$

where N_{p} is the prediction horizon and N_{c} is the control horizon. $x(k+i|k)$ and $u(k+i|k)$ refer to the open-loop predictive state and control quantity at time point k, respectively.

To obtain a manageable optimization problem, the cost function can be defined as follows:

$$J(\xi(k), u(k-1), \Delta u(k)) = \sum_{i=1}^{N_p} \left\|\eta(k+i|k) - \eta_{ref}(k+i|k)\right\|_Q^2 + \sum_{i=1}^{N_c-1} \|\Delta u(k+i|k)\|_R^2, \tag{11}$$

where $\boldsymbol{\eta}_{\mathrm{ref}}(k+i|k)$ represents the reference vector and $\mathbf{Q}$ and $\mathbf{R}$ are weighting matrices of objectives and control, respectively. In the car-following problem, they are defined as follows:

$$\begin{aligned}
\boldsymbol{\eta}_{\mathrm{ref}}(k+i|k) &= [\Delta d_{\mathrm{des}}(k+i|k) \ \ 0 \ \ 0 \ \ 0]^{\mathrm{T}}, \\
\Delta u(k+i|k) &= j(k+i|k)\Delta t, \\
\mathbf{Q} &= \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},
\end{aligned} \tag{12}$$

where $\mathbf{R}$ is a one-dimensional vector, $R = 10$.

The optimization objectives together with the constraints of MPC are

$$s.t. \begin{cases} d_0 \le \Delta d(k) \le d_{\max}, \\ v_{\min} \le v(k) \le v_{\max}, \\ a_{\min} \le a(k) \le a_{\max}, \\ j_{\min} \le j(k) \le j_{\max}. \end{cases} \tag{13}$$

5. Simulation Results

In this section, the performance of the proposed car-following model is evaluated and the differences between conservative and aggressive driving styles are analyzed. All the investigations are based on testing data, and no collisions occurred for both conservative and aggressive car-following modes. The distribution of time to collision (TTC), jerk, and time headway are used to compare the performance of different models in safety, comfort, and driving efficiency.

5.1. Safety. In traffic flow research, TTC is used to represent safety and is defined as the opposite of the ratio of inter-vehicle distance to relative speed. Obviously, the larger the

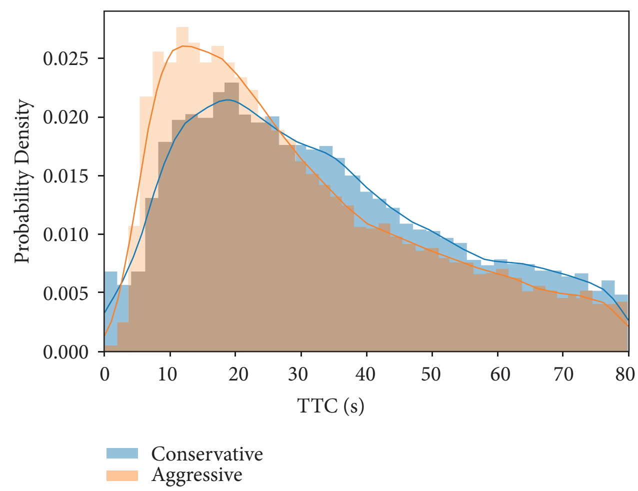


Figure 5: TTC distributions in terms of models.

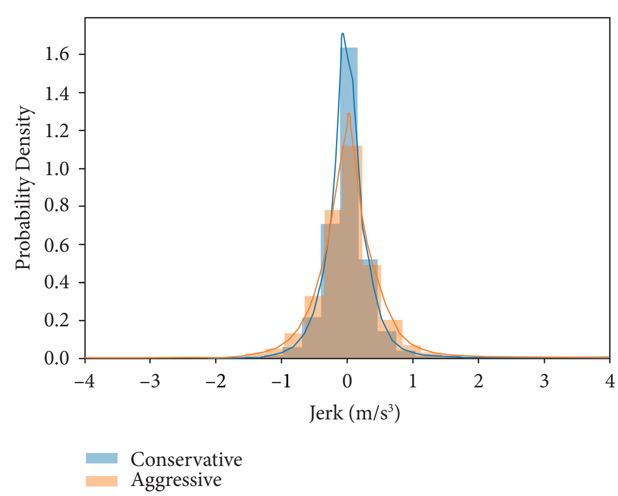


Figure 6: Jerk distributions in terms of models.

TTC value is, the safer it is. Figure 5 shows the distribution of TTC for conservative and aggressive driving model simulations. Only the values between 0 and 80 s are counted, and some invalid data are eliminated. The mean value of the TTC is approximately 33.36 s in the conservative driving style and approximately 29.85 s in the aggressive driving style. This shows that the driving behavior produced by the conservative driving style model is safer than that produced by the aggressive driving style model.

5.2. Comfort. A large absolute value of jerk indicates that the comfort is low. Figure 6 compares the distribution of jerk for conservative and aggressive driving style model simulations. It can be noted that the jerk values generated by the conservative and aggressive driving style models are concentrated between −2 and 2 m/s^3. The means of the absolute value of jerk are 0.28 and 0.38 m/s^3, respectively. It can be concluded that the comfort of the conservative driving model is higher than that of the aggressive driving model.

5.3. Driving Efficiency. Figure 7 shows the distribution of time headway under the conservative and aggressive driving models. The time headway can reflect the driving efficiency to a certain extent; that is, the smaller the time headway, the higher the driving efficiency. As can be seen from the figure, the time headway under the aggressive driving style is maintained at approximately 2.4 s, while that under the conservative driving style is maintained at 4.0 s. This shows that the aggressive driving style has higher driving efficiency than the conservative driving style.

Two car-following scenes were randomly chosen from the testing data. Because the speed of the FV is closely related to the speed of the LV, it cannot reflect the driver's style well, so in this work, the inter-vehicle distance, acceleration, and jerk were selected to compare the performance of different driving styles. Figures 8 and 9 show the observed inter-vehicle distance, acceleration, and jerk generated by different driver car-following models. It can be seen that under different car-following models, the inter-vehicle distance acceleration and jerk are significantly different. The

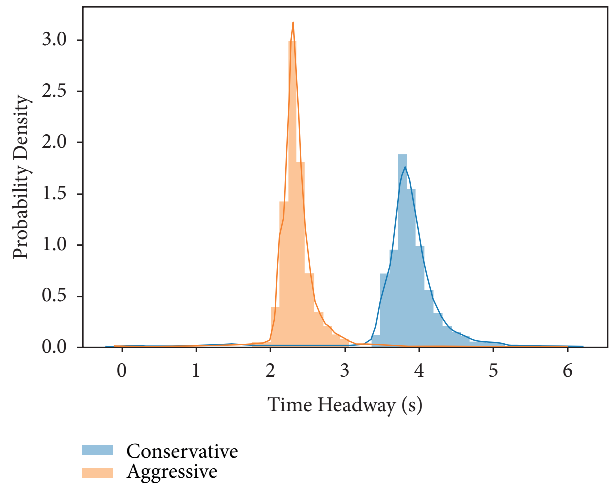


Figure 7: Time headway distributions in terms of models.

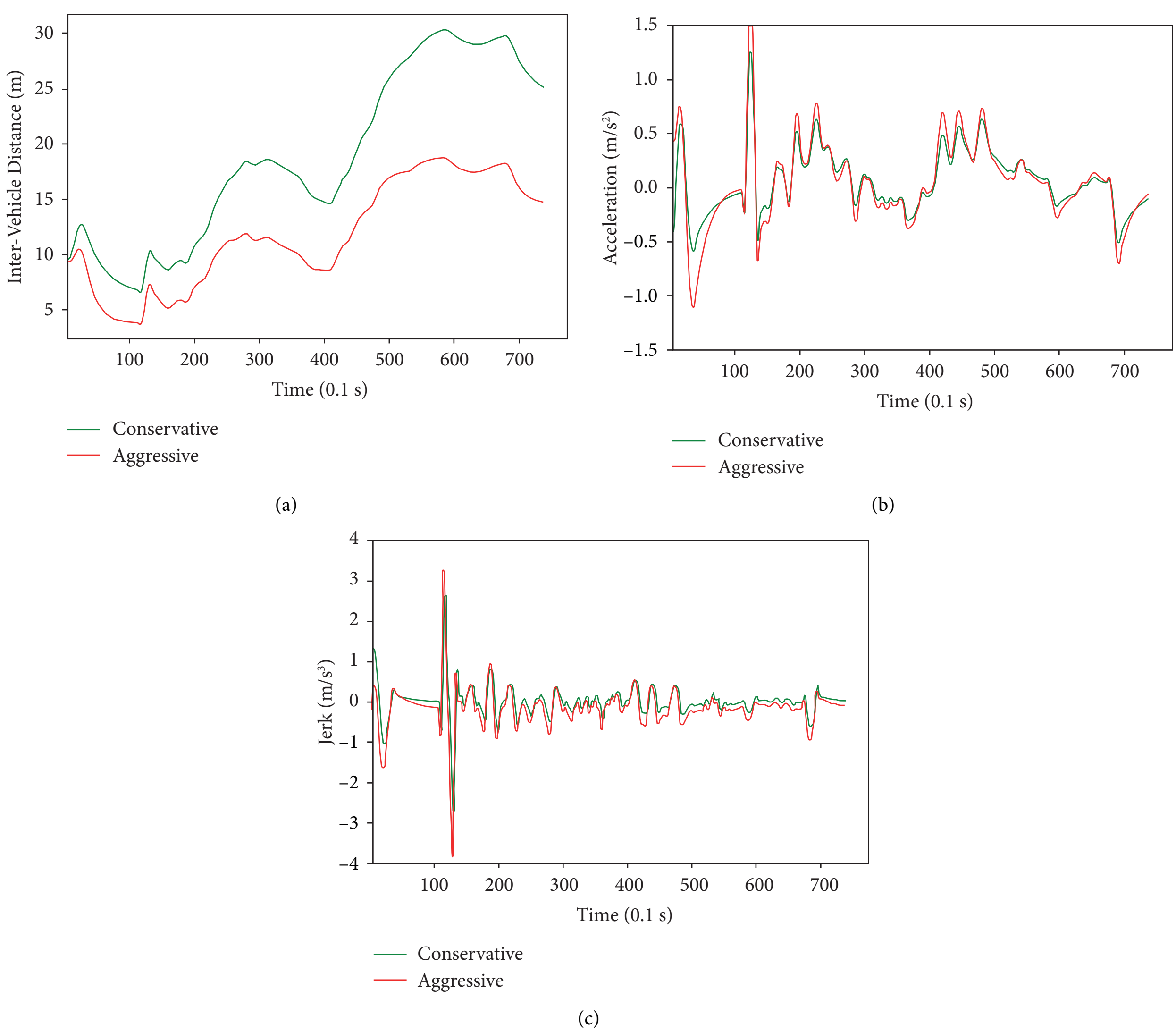


Figure 8: #1 Randomly chosen car-following events from testing data for comparing the performance of different driving styles: (a) intervehicle distance, (b) acceleration, and (c) jerk curves.

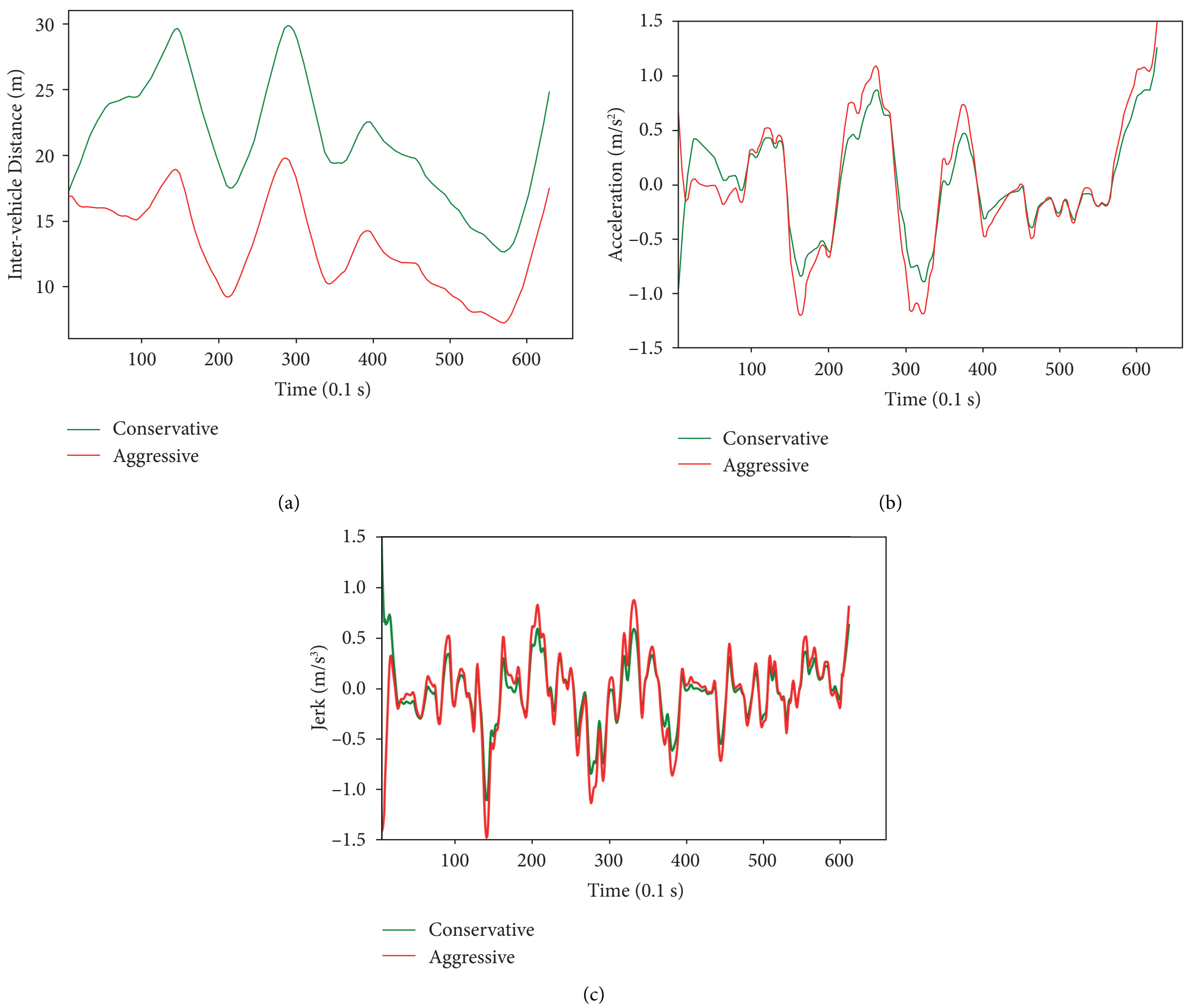


FIGURE 9: #2 Randomly chosen car-following events from testing data for comparing the performance of different driving styles: (a) intervehicle distance, (b) acceleration, and (c) jerk curves.

conservative model maintains a larger inter-vehicle distance and a smaller range of acceleration and jerk fluctuations; the aggressive model maintains a smaller inter-vehicle distance and a larger range of acceleration and jerk fluctuations.

Based on the results discussed above, it can be concluded that the proposed different styles of car-following models show different levels of safety, comfort, and efficiency in the same car-following scene.

6. Conclusions

This study proposed a car-following model considering different driving styles. The model was based on an MPC algorithm, and the design parameters of different styles of models were derived from NGSIM data. The behavior of the proposed model was analyzed in experiments, the results of which showed that different driving style models exhibited different levels of safety, comfort, and effectiveness when following a lead vehicle. Compared to the radical driving model, the conservative driving model is safer and more comfortable; however, its driving efficiency is low.

Our planned future study will focus on three aspects of this research. First, road traffic efficiency will be considered to maintain the inter-vehicle distance in a more reasonable range. Our second objective will be to classify driving styles in more detail to provide users with more choices. Finally, we plan to design the driver model combined with the executive ability of the lower controller to ensure that the designed model is more reasonable and practical.

Data Availability

The data were obtained from the Next Generation Simulation (NGSIM).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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