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Research article

Human-like car-following modeling based on online driving style recognition

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Abstract: Incorporating human driving style into car-following modeling is critical for achieving higher levels of driving automation. By capturing the characteristics of human driving, it can lead to a more natural and seamless transition from human-driven to automated driving. A clustering approach is introduced that utilized principal component analysis (PCA) and k-means clustering algorithm to identify driving style types such as aggressive, moderate and conservative at the timestep level. Additionally, an online driving style recognition technique is developed based on the memory effect in driving behavior, allowing for real-time identification of a driver's driving style and enabling adaptive control in automated driving. Finally, the Intelligent Driver Model (IDM) has been improved through the incorporation of an online driving style recognition strategy into car-following modeling, resulting in a human-like IDM that emulates real-world driving behaviors. This enhancement has important implications for the field of automated driving, as it allows for greater accuracy and adaptability in modeling human driving behavior and may ultimately lead to more effective and seamless transitions between human-driven and automated driving modes. The results show that the time-step level driving style recognition method provides a more precise understanding of driving styles that accounts for both inter-driver heterogeneity and intra-driver variation. The proposed human-like IDM performs well in capturing driving style characteristics and reproducing driving behavior. The stability of this improved human-like IDM is also confirmed, indicating its reliability and effectiveness. Overall, the research suggests that the proposed model has promising performance and potential applications in the field of automated driving.

Keywords: driving style; machine learning; car-following model; memory effect; genetic algorithm; string stability

1. Introduction

Driving automation has become a highly focused topic in recent years. Its development can be classified into six levels, according to SAE International [1]. The currently on-road advanced driver assistance system and traffic jam chauffeur are at Levels 2 and 3. These automation technologies are installed in newly sold commercial vehicles to increase traffic safety and efficiency. For the state-of-the-art intelligent system, providing a smooth driving experience to human drivers is a vital target. It requires a deeper understanding of human driver behavior to achieve better human-computer interaction. This statement is supported by studies, which designed personalized intelligent systems based on different driving styles [2–6]. This kind of human-like driving strategy not only promotes the performance of driving automation but also improves driver acceptability of intelligent systems by adapting to human driver preferences.

Car-following is the most common driving scenario in heavy traffic, which puts much workload on drivers. The intelligent systems enable the driver to maintain a safe and comfortable following state and improve traffic capacity. Their performance optimization requires intensive research on car-following behavior modeling. Over the past several decades, numerous car-following models have been developed [7–9], and most of them are constructed and calibrated based on the overall driving characteristics. Recently, personalized car-following models have been raised considering different driving styles. Some of them emphasize the difference between individual drivers in driving style characteristics [10–20]. Others suggest that the driving style is influenced by driving conditions such as environment, driving needs and traffic situations, as well as drivers' personalities [3, 8, 21–26]. Although the personalized car-following models based on driving style improve the performance of driving automation, the investigation of driving style remains insufficient. The investigation of driving style in personalized car-following models is limited by a focus on inter-driver heterogeneity rather than intra-driver variations, the use of broad statistical values for classification and the lack of real-time driving style recognition to enable human-like driving automation. Moreover, considering the high interpretability of the Intelligent Driver Model (IDM), several studies have incorporated driving heterogeneity into this classic model [21, 25–28]. However, stability analysis for the modified models is often overlooked. It is essential to conduct stability analysis when adapting and enhancing car-following models to ensure reliability, performance and safety in real-world traffic scenarios.

To address the above limitations, we propose a driving style recognition process and apply it to human-like car-following modeling. The main contributions are twofold: (i) A time-step level driving style recognition method is developed, taking into account not only the inter-driver heterogeneity but also the intra-driver variation and the memory effect of drivers. This method allows for a more accurate and nuanced understanding of driving styles. (ii) By incorporating the online driving style recognition strategy into car-following modeling, the original Intelligent Driver Model (IDM) is enhanced to a human-like IDM resembling real-world driving behaviors. The stability of this improved human-like IDM is verified, ensuring its reliability and effectiveness in longitudinal control.

The rest of this paper is organized as follows. Section 2 reviews the related work. Section 3 proposes the methodology, including driving style clustering, online driving style recognition, the human-like car-following modeling and the stability analysis. The experimental results of driving style recognition and human-like car-following modeling are presented in Section 4. Our findings are concluded in Section 5.

2. Literature review

For decades, studies have been carried out to recognize the variations in driving styles between drivers. As early as 2007, Ishibashi et al. [29] emphasized the importance of understanding driver behavior in developing driver support systems. They introduced a Driving Style Questionnaire (DSQ) to characterize drivers and examined its validity through an analysis of car-following behavior at low speed. In 2017, Martinez et al. [3] provided a survey on driving style characterization and recognition, focusing on machine learning approaches based on current and future trends. The survey also presented a brief discussion on the applications of driving style recognition to intelligent vehicle controls, along with predictions of future development from experts in the field. Zhu et al. [12], by analyzing cluster displays of driving behavior diversity, found that aggressive drivers had shorter mean gaps than conservative drivers, while maintaining similar following speeds. Xue et al. [13] implemented support vector machine (SVM) and discrete wavelet transform (DWT) feature extraction techniques to distinguish between various driving styles. Time headway and acceleration/deceleration parameters were then adjusted according to the driving styles to better represent real-world car-following behavior for different driving styles.

Based on the aforementioned studies, research on personalized driver assistance systems and driving behavior analysis has made significant progress. Miyajima et al. [10] focused on individual differences in car-following behavior and pedal operation patterns. Utilizing the optimal velocity model and Gaussian mixture model, distinct driving styles were captured, facilitating the personalization of intelligent driver assistance systems. Wang et al. [11] introduced a self-learning algorithm for online model identification aimed at enhancing driver acceptance of longitudinal advanced driver assistance systems. Zhu et al. [14] employed a Gaussian mixture model (GMM) to fit each driver's driving data and utilized Kullback-Leibler (KL) divergence to assess the similarity among drivers based on their GMMs. An unsupervised clustering algorithm was then proposed to group human drivers into three categories according to the similarities measured by KL divergence. Driving style was integrated into car-following modeling by developing a personalized fully-adaptive cruise control system reflecting diverse driving styles. Gao et al. [15] employed unsupervised machine learning methods, namely K-means clustering and self-organizing map (SOM) neural network, to group drivers according to their driving styles. Utilizing the clustering results, a supervised machine learning technique, specifically, support vector machine (SVM), was implemented to design an online driving style classifier. This classifier was embedded into the front-end of the upper controller of a personalized adaptive cruise control system. Chu et al. [16] introduced a reinforcement learning-based car-following style learning algorithm to identify individual car-following styles and adapt the proposed optimal cruise controller accordingly. This method enables personalized control behavior, aligning more closely with individual driver preferences and habits, and yielding control behavior more akin to a human driver compared to factory-installed adaptive cruise control. Hu and Luo [17] established a model utilizing a neural network-based learning control paradigm and car-following data, designed to track relative speed and distance at a personal, sustainable level. Through quantitative analysis and k-means clustering, it was demonstrated that the car-following model possesses the ability to retain and reproduce naturalistic driving styles.

Over the past two years, there has been continued interest in developing personalized car-following models. By analyzing urban electric vehicle driving data, Hu et al. [18] examined different driving styles and their respective characteristics and proposed an optimization method for assigning weight coefficients to these driving styles. Sheng et al. [19] utilized model-free inverse reinforcement learning to examine 42 drivers' styles and classified them into four groups. The study integrated driving styles into car-following modeling by creating a personalized adaptive cruise control (P-ACC) system using a partially observable Markov decision process (POMDP) model. Liao et al. [20] developed a personalized car-following model using a memory-based deep reinforcement learning approach. The study integrated twin delayed deep deterministic policy gradients (TD3) with a long short-term memory (LSTM) to create the LSTM-TD3 model, which adapts to human driving habits and improves upon traditional methods of modeling car-following behavior.

However, research has also shown that intra-driver variations exist, besides the differences in driving style between drivers. Driving style is influenced not only by individual drivers' personalities but also by factors such as environmental conditions, driving needs and traffic conditions. Treiber et al. [21] explored the extensive variation of driving styles depending on the local speed variation coefficient, representing an early study that considered intra-driver changes in driving style. Dörr et al. [22] presented an online driving style recognition system that uses fuzzy logic to identify the current driving style of the driver. Berthaume et al. [24] incorporated driving style into car-following modeling by analyzing car-following behavior heterogeneity as a function of road type and traffic condition. Chen et al. [25] integrated driving style into two classical car-following models (IDM and Gipps' model) by introducing a Long-term and Short-term Driving (LSTD) model. The K-means clustering algorithm was employed to classify long-term driving characteristics, while concepts from personality trait theory were utilized to categorize short-term driving characteristics based on their stability or instability over time. Sun et al. [26] used a fuzzy inference system to categorize freeway car-following events into two styles: non-aggressive and aggressive. The car-following models (Gipps, Wiedemann and IDM) were calibrated and validated for each driving style group. By analyzing the percentage of driving style events for each driver, it was found that most drivers did not always maintain one driving style when following vehicles.

In brief, as the field of driving style research has evolved, researchers have developed various approaches and techniques to capture and analyze these differences. Machine learning algorithms, including clustering methods and neural networks, have been employed to classify driving styles and develop personalized driving assistance systems. Integration of driving styles into car-following modeling has also been a significant area of focus, leading to the development of personalized adaptive cruise control systems and other driver assistance technologies.

3. Methodology

3.1. Architecture

Human-like driving automation can be achieved by applying the driving style clustering and recognition process to car-following modeling. Figure 1 presents the framework overview. It can be seen that the scheme is conducted on the basis of a driving database. First, the driving style clustering algorithm is exploited based on the training set. Then, on the one hand, the clustering evolves into online recognition considering the memory effect of driving behavior. On the other hand, the clustering results are adopted as the training set to design a human-like car-following model. The Human-like Intelligent Driver Model (HIDM) is developed to adapt to different driving styles. Finally, the proposed car-following model is validated with the testing set in the simulation environment. Based on this framework, the operation mode can switch automatically to match the appropriate driving style.

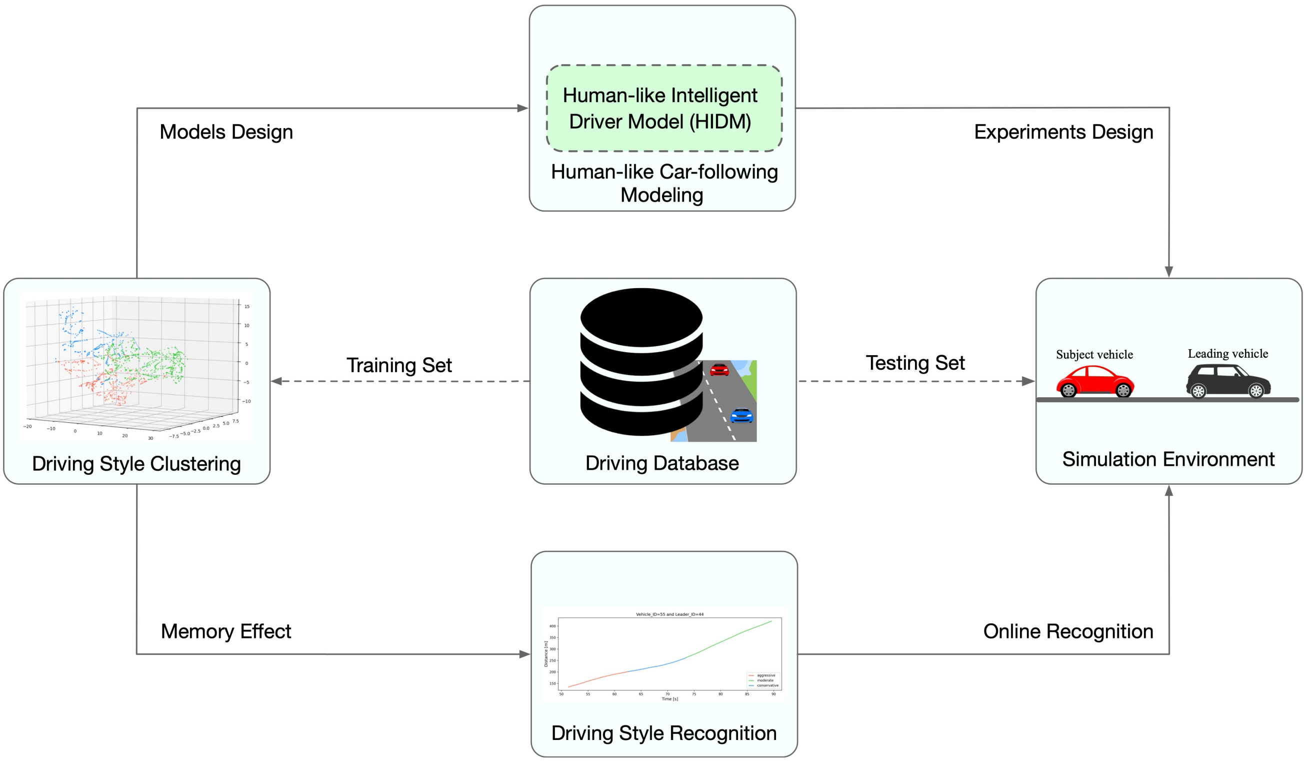


Figure 1. Framework overview.

3.2. Driving style

3.2.1. Definition of driving style

Driving style is a complex concept involving many factors, such as driver type, driver condition, driving situation and travel purpose [22]. In 1993, Elander et al. [30] recognized drivers' individual differences, defining driving style as personal choices and driving habits. Ishibashi et al. [29] investigated driving style with questionnaires, focusing on ways of thinking of drivers. Dörr et al. [22] defined driving style as the manner in which the driving task is executed by the driver, manifested by the driver's manner of vehicle operation. Sagberg et al. [23] reviewed the definition of driving style in previous research and included both consciously preferred actions and subconscious habits of drivers in the description. Martinez et al. [3] distinguished related terms and suggested that driving style is the way the driver operates a vehicle in the context of the driving scene and external conditions. It is emphasized that the same driver could exhibit disparate styles under different driving conditions. This concept is accepted by follow-up studies [26, 31–36], which conducted related research on driving style. Chen et al. [25] suggested that the driving style has time-varying nature in the short-term and explored the temporarily changing characteristics after external stimuli and psychological fluctuation. Consistent with this concept, we also focus on the variation of driving style during the driving process. However, we emphasize the disparate driving styles adopted by human drivers under different traffic conditions, aiming at human-like driving automation.

3.2.2. Driving style labels

Classification labeling is a crucial issue in driving style analysis. Most studies classified driving styles into discrete classes [3]. Table 1 summarizes the survey of classification options in recent research. These options are inspired by the consideration from different perspectives, such as traffic safety, efficiency and fuel economy. In general, the number of categories varies from 2 to 4.

Table 1. Classification labeling of driving styles.

Researchers	Labels
Aljaafreh et al. [37]	below normal, normal, aggressive, very aggressive
Dörr et al. [22]	comfortable, normal, sporty
Zhu et al. [12]	aggressive, conservative
Xue et al. [13]	normal, aggressive
Zhu et al. [14]	aggressive, normal, cautious
Chen et al. [25]	long-term (timid, neutral, aggressive), short-term (unstable, stable)
Gao et al. [15]	conservative, moderate, aggressive
Hu and Luo [17]	mild, moderate, aggressive
Sun et al. [26]	aggressive, non-aggressive
Hu et al. [18]	aggressive, cautious, standard
Liao et al. [20]	aggressive, common, conservative

Although a larger number of categories can classify driving styles more elaborately, it complicates algorithm development and interpretation of the classes. From the labels exhibited in Table 1, it can be seen that studies tend to label driving styles as aggressive, moderate and conservative, even if the expressions differ. Therefore, driving styles are grouped into these three types in this study.

3.3. Driving style clustering algorithm

3.3.1. Characteristic variables

Determining the characteristic variables of driving style is the initial step for driving style recognition. Choosing appropriate characteristic variables is crucial for robust classification. There is no general consensus on the selection of variables [3]. A summary of the characteristic variables is listed in Table 2.

Table 2. Characteristic variables list.

Researchers	Characteristic variables
Miyajima et al. [10]	the relationship between following distance and velocity, gas and brake pedal operation
Aljaafreh et al. [37]	acceleration, speed
Wang et al. [11]	time headway, time to collision
Zhu et al. [12]	speed, gap, relative speed
Yang et al. [38]	longitudinal acceleration, lateral acceleration, degree of acceleration pedal, force of brake pedal, head deviation, space headway, time headway, lane deviation, distance to the yellow line, steering wheel angle, speed, relative speed, acceleration, deceleration
Xue et al. [13]	acceleration, relative distance, relative velocity
Chen et al. [25]	acceleration, deceleration, time headway
Gao et al. [15]	relative speed, time headway, jerk
Sun et al. [26]	gap, speed, acceleration, deceleration
Hu et al. [18]	velocity, acceleration and deceleration, position of accelerator pedal, time ratio of brake pedal
Liao et al. [20]	time headway, time to collision

The table shows that trajectory-based variables are the commonly used characteristics, such as gap, speed, etc., which carry enough information to describe the differences in driving style. Therefore, we extract variables from trajectory data as much as possible to characterize the driving style in car-following, including gap distance, relative speed, speed, acceleration (deceleration), time headway and jerk. Note that time to collision (TTC) is not included in the variables, as it is a warning indicator that may have little significance if it exceeds a certain threshold.

Except for time headway and jerk, other variables can be obtained from sample data directly. Time headway (THW) is the time difference between the leading and following vehicles passing through the same location. It can be calculated by dividing the vehicles' space headway by the following vehicle's speed, as in Eq (3.1). Here, space headway refers to the distance between the front bumpers of adjacent vehicles, which is the sum of the gap distance and the length of the leading vehicle. Jerk is the change rate of acceleration, which can reflect the intensity of acceleration or deceleration, as formulated in Eq (3.2).

$$thw_n(t) = \frac{\Delta x_n(t) + l_{n-1}}{v_n(t)} \tag{3.1}$$

$$jerk_n(t) = \frac{a_n(t) - a_n(t-1)}{dt} \tag{3.2}$$

3.3.2. Algorithm

As all the possible influencing variables are collected for a comprehensive analysis, it will result in richer research but may lead to redundant data and complex calculations. Furthermore, unsupervised learning methods are required to cluster the driving styles since there are no labeled driving styles in the training data. That is, the algorithm needs to discover the similarities inside the input variables and distinguish driving styles into groups without the guidance of existing labeling samples. Therefore, we propose a clustering process that combines principal component analysis (PCA) and k-means clustering.

PCA is a dimensionality reduction method that can extract and simplify data description while preserving as much variation in the original data as possible [39]. It utilizes orthogonal transformation to convert a series of possibly linearly related variables into a set of linearly unrelated new variables, also known as principal components (PCs). Namely, PCs are linear combinations of the original variables, and the number of PCs is not more than the original variables. Their meanings are different from the original ones but contain all the information of the data. The latent variables for further analysis can be picked out by the contribution rate of PCs, which include most of the characteristics and have lower dimensions. We use PCA to summarize and understand the underlying structure of driving trajectory data and find low-dimensional representations of characteristic variables. Then, we apply the k-means algorithm [40] to cluster driving styles. The k-means algorithm is a typical partitioning method that finds a partition to keep the samples within the same cluster close to each other. It inputs the latent variables and outputs driving style clusters. The procedure is designed in detail, as presented in Algorithm 1 below. The number of desired clusters k is 3, corresponding to the three types of driving styles, aggressive, moderate and conservative.

3.4. Online driving style recognition

With the above driving style clustering algorithm, we can identify the driving style types at every timestep, and one timestep here represents 0.1 s according to our trajectory data. However, operating the vehicle based on the instantaneous driving style is inappropriate. As drivers' decision-making is

Algorithm 1: K-means clustering for driving styles

Input: The latent variables $D = \{x_1, x_2, ..., x_m\}$;
the number of desired clusters k.
Steps:
Initialize k cluster centroids randomly $\{\mu_1, \mu_2, ..., \mu_k\}$;
repeat
  Initialize clusters $C_i = \varnothing (1 \leq i \leq k)$;
  for $j = 1, 2, ..., m$ **do**
    Calculate the Euclidean distance to each centroid $\mu_i (1 \leq i \leq k)$: $d_{ji} = \left\| x_j - \mu_i \right\|_2$;
    Label x_j with the nearest cluster: $\lambda_j = \arg\min_{i \in \{1,2,...,k\}}$;
    Assign x_j to that cluster: $C_{\lambda_j} = C_{\lambda_j} \cup \{x_j\}$;
  end
  for $i = 1, 2, ..., k$ **do**
    Recalculate the cluster centroid: $\mu'_i = \frac{1}{|C_i|} \sum_{x \in C_i} x$;
    if $\mu'_i \neq \mu_i$ **then**
      Update the cluster centroid from μ_i to $\mu' i$;
    else
      Keep the cluster centroid unchanged;
    end
  end
until *convergence criteria is met*;
Output: Set of k driving style clusters $C = \{C_1, C_2, ..., C_k\}$

influenced by historical driving behaviors and past traffic states [41], the memory effect is considered to be an indispensable factor for car-following modeling [20, 42–47]. Therefore, we propose online driving style recognition based on the sliding window technique to incorporate the memory effect into car-following modeling and avoid unrealistic driving style switching.

The sliding window technique is a computational method frequently used in time series data analysis. The window includes contiguous blocks of fixed size and can slide forward to complete a particular task. Figure 2 illustrates its utilization in online driving style recognition. The lattices stand for timesteps, and the colors filled in represent the driving styles identified by the clustering algorithm. The window will slide forward by one timestep to complete the online driving style recognition. For the timestep t, we consider its previous timesteps ranging from $t - t_m + 1$ to $t - 1$ as memory, where t_m is the length of memory.

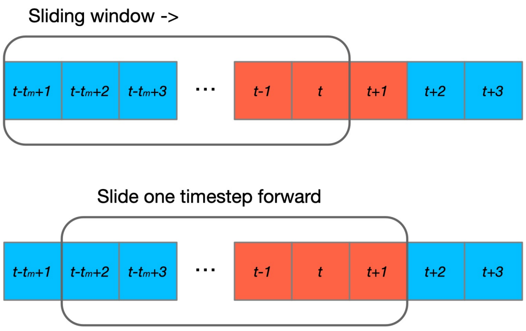


Figure 2. Sliding window technique for online driving style recognition.

The online recognition result of driving style at the t th timestep, i.e., $type^*(t)$, will be the guidance for vehicle operation, which is determined by the statistical analysis of driving styles in the window, as formulated in Eq (3.3).

$$type^*(t) = \arg\max \ f(\{type(t) : t \in (t - t_m, t]\}) \tag{3.3}$$

where $type(t)$ represents the driving style clustering result at timestep t. $f(\cdot)$ is the frequency counter for types in the window.

3.5. Human-like Intelligent Driver Model (HIDM)

The original Intelligent Driver Model (IDM) was proposed by Treiber et al. [48] to simulate traffic congestion. It is also utilized to develop adaptive cruise control (ACC), adapting to different traffic situations [49], which proves to be traffic efficient. Since IDM is generally acknowledged as one of the best-performing car-following models [8], we propose the Human-like Intelligent Driver Model (HIDM) by extending IDM with online driving style recognition strategy.

The IDM acceleration, denoted as $\dot{v}$, is given as follows:

$$\dot{v}(\Delta x, v, \Delta v) = \tilde{a}\left[1 - \left(\frac{v}{\tilde{v}}\right)^4 - \left(\frac{S(v, \Delta v)}{\Delta x}\right)^2\right] \tag{3.4}$$

$$S(v, \Delta v) = s_0 + t_0 v - \frac{v \Delta v}{2\sqrt{\tilde{a}\tilde{b}}} \tag{3.5}$$

where $S(v, \Delta v)$ denotes the desired gap function, which is calculated from speed and relative speed. Five parameters need to be calibrated, maximum acceleration ($\tilde{a}$), comfortable deceleration ($\tilde{b}$), desired speed ($\tilde{v}$), desired time gap (t_0) and minimum gap (s_0).

We define a parameter vector, represented as $\theta = [\tilde{a}, \tilde{b}, \tilde{v}, t_0, s_0]$. This parameter vector is responsible for setting the instantaneous parameter vector, denoted as $\theta(t)$, at timestep t based on the driving style type at that specific timestep, as represented by Eq (3.6).

$$\theta(t) = \begin{cases} \theta_{agg}, & type^*(t) = aggressive \\ \theta_{mod}, & type^*(t) = moderate \\ \theta_{con}, & type^*(t) = conservative \end{cases} \tag{3.6}$$

where θ_{agg}, θ_{mod} and θ_{con} are the parameter vectors of the three driving style types, respectively, which will be calibrated separately with the clustered training data.

The proposed Human-like Intelligent Driver Model (HIDM) is designed to incorporate real-time driving style recognition. The HIDM acceleration function is denoted as $\dot{v}(\Delta x, v, \Delta v; \theta(t))$. The parameter vector $\theta(t)$ depends on the value of the ternary discrete variable driving style, which is adjusted according to the current driving style type at each timestep.

3.6. String stability analysis

Traffic flow stability refers to its ability to maintain a balanced state, which is related to the efficiency and safety of the traffic system. As an important microscopic feature of traffic flow, the stability of vehicle-following models has attracted extensive attention from scholars since the inception of the models [50]. Generally speaking, there are two types of stability analysis: linear stability analysis and nonlinear stability analysis [51]. Linear stability analysis focuses on the stability characteristics of the system under the influence of small disturbances, while nonlinear stability analysis focuses on the stability characteristics of the system under the influence of large disturbances. For actual road traffic flow, road users experience minimal disturbance, and nonlinear following models are usually linearized near the equilibrium point, so linear stability analysis has been the focus of traffic flow theory research. Linear stability is divided into two types: local stability and string stability [51]. Local stability focuses on the stability of individual vehicles under small disturbances; string stability studies how a small disturbance in one vehicle propagates along the convoy and affects the stability of the entire convoy. As the extended following models are usually based on a refined framework, local stability remains unchanged [50]. Therefore, the traffic flow theory research community tends to focus closely on string stability. From the perspective of traffic operation, it is desirable to minimize or avoid string instability. However, from a modeling perspective, realistic traffic flow models should be able to describe string instability in order to reproduce features related to traffic oscillations.

Ward [52] assumed that there are small disturbances in the headway and speed of vehicles in an infinitely long convoy and derived the instability conditions for traffic flow. Some studies [50, 53–57] have conducted stability analysis of following models guided by the general framework developed by Ward and Wilson [52, 58], verifying the effectiveness of the framework. In this paper, we examine the string stability of the proposed HIDM, adhering to the general framework.

Both IDM and HIDM can be represented by a control equation, as in Eq (3.7). When the traffic flow is running under an equilibrium situation, the vehicle acceleration (the derivative of speed) and relative speed are zeros (i.e., $\dot{v} = 0, \Delta v = 0$), and the gap distance and speed have equilibrium solutions (i.e., $\Delta x = \Delta x^e, v = v^e$), as the transformation presented in Eq (3.8).

$$\dot{v} = f(\Delta x, v, \Delta v) \tag{3.7}$$

$$f(\Delta x^e, v^e, 0) = 0 \tag{3.8}$$

The instability equation was deduced by Ward [52] assuming a small perturbation occurred in the equilibrium state, as formulated in Eq (3.9).

$$\frac{1}{2}(f_v)^2 - f_{\Delta v} f_v - f_{\Delta x} < 0 \tag{3.9}$$

where f_v, $f_{\Delta v}$ and $f_{\Delta x}$ are the partial derivatives of the control equation for speed, relative speed and gap distance, as expanded in Eq (3.10).

$$\begin{cases} f_{\Delta x} = \dfrac{\partial f(\Delta x, v, \Delta v)}{\partial h}\Big|_{(\Delta x^e, v^e, 0)} \\ f_v = \dfrac{\partial f(\Delta x, v, \Delta v)}{\partial v}\Big|_{(\Delta x^e, v^e, 0)} \\ f_{\Delta v} = \dfrac{\partial f(\Delta x, v, \Delta v)}{\partial \Delta v}\Big|_{(\Delta x^e, v^e, 0)} \end{cases} \tag{3.10}$$

The partial differential equations of both IDM and HIDM are derived from Eqs (3.4) and (3.5), as presented in Eq (3.11). The values of parameters (i.e., $\tilde{a}, \tilde{b}, \tilde{v}, t_0, s_0$) are different for IDM and HIDM, as explained in the above section.

$$
\begin{cases}
f_{\Delta x} = 2\tilde{a}\dfrac{(s_0 + t_0 v^e)^2}{\Delta x^{e3}} \\
f_v = -2\tilde{a}\left[\dfrac{2}{\tilde{v}}\left(\dfrac{v^e}{\tilde{v}}\right)^3 + \dfrac{t_0(s_0 + t_0 v^e)}{\Delta x^{e2}}\right] \\
f_{\Delta v} = \sqrt{\dfrac{\tilde{a}}{\tilde{b}}}\dfrac{v^e(s_0 + t_0 v^e)}{\Delta x^{e2}}
\end{cases}
\tag{3.11}
$$

Therefore, combining Eqs (3.9) and (3.11), the string stability of IDM and HIDM can be analyzed. The experiment of analytical solution will be conducted with calibrated parameters and exhibited in the next section.

4. Experiments

4.1. Data preparation

The NGSIM datasets [59] are detailed and high-fidelity traffic datasets collected from real-world vehicle trajectory data by the Next Generation SIMulation (NGSIM) computer program. They are popularly used for traffic analysis and microsimulation research to enhance the applicability of traffic models. The Interstate 80 (I-80) freeway dataset was one of several datasets collected under the NGSIM program. It was organized on eastbound I-80 in the San Francisco Bay area in Emeryville, California, on April 13, 2005. The dataset includes three 15-minute periods, representing congestion buildup (the transition between uncongested and congested conditions) and complete congestion during the peak period. The study area is approximately 400 meters in length. Lane 1 is the high-occupancy vehicle (HOV) lane, so its traffic may not be typical. We will only study the vehicles on the other five regular routes (from Lane 2 to Lane 6).

As investigated by Punzo et al. [60], the original dataset has measurement errors, and the errors have adverse effects on microscopic traffic research, such as model calibration and simulation. Montanino and Punzo [61] proposed a "traffic-informed" method and applied it to NGSIM reconstruction to ensure that the reconstructed trajectory data is consistent with vehicle kinematics and microscopic traffic dynamics. In this paper, we adopt the reconstructed NGSIM I-80 dataset (from 4:00 to 4:15 p.m.). Since only longitudinal control is examined in this research, we extract car-following events that last continuously for no less than 30 s (300 timesteps, 10 Hz data resolution) to eliminate the influence of lateral behavior. We obtain 1386 car-following events involving 662,378 trajectory data points. Each data point contains trajectory information at that timestep. Figure 3 shows the speed and acceleration profiles of the subject vehicle from a randomly selected car-following event and also displays the comparison of the raw data and cleaned data.

The car-following events need to be separated into two parts for training and testing. To meet the demand for complete independence of the testing process, we select the car-following events collected from Lane 2 as the testing set, i.e., 167,975 trajectory data points (332 vehicle pairs). The events left (from Lane 3 to Lane 6) will be used as the training set, including 494,403 trajectory data points from 1054 vehicle pairs.

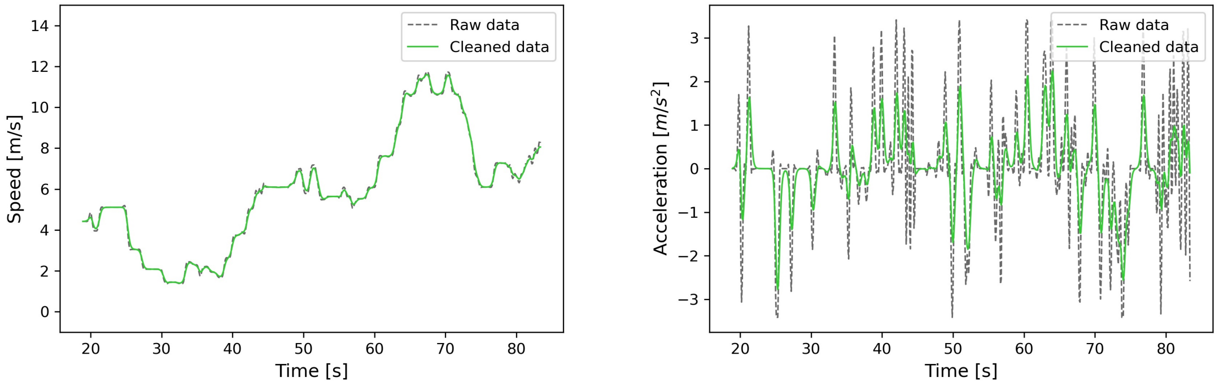


Figure 3. Speed and acceleration profiles comparing raw data with cleaned data (Vehicle_ID=11).

4.2. Driving style clustering and visualizing

The clustering process, which combines PCA and k-means, is conducted using the scikit-learn library in Python. Standardization is applied to the six characteristic variables of the 494,403 training samples, and PCA is performed on the standardized matrix. The table presented in Table 3 displays the principal components (PCs) and their corresponding contribution rates. The table highlights that the first five PCs have a cumulative contribution rate greater than 95%, indicating that they effectively represent the original driving style characteristics. The k-means clustering algorithm takes the first five PCs as input and subsequently outputs three clustering sets.

Table 3. Results of principle components (PCs).

Principal components	Contribution rate	Cumulated contribution rate
P_1	0.319	0.319
P_2	0.226	0.545
P_3	0.185	0.730
P_4	0.143	0.873
P_5	0.114	0.987
P_6	0.013	1.000

The driving style clustering input has six characteristics (gap distance, relative speed, speed, acceleration, time headway and jerk). It is good to understand the driving style comprehensively, but it is hard to visualize the clustering results in six dimensions. The t-distributed stochastic neighbor embedding (t-SNE) algorithm [62] is a nonlinear dimensionality reduction technique ideal for embedding high-dimensional data into a low-dimensional space in two or three dimensions for visualization. To avoid having too many samples, making it difficult to see the points, we randomly select some car-following events for visualization. By applying the t-SNE algorithm, the six-dimensional characteristic variables are reduced to three dimensions, and these three dimensions are merged with the clustering output. The visualization result is shown in Figure 5, where the axes of x, y and z are the three reduced dimensions with no practical meanings. It shows that the three types of driving styles (aggressive, moderate and conservative) have distinction, which implies the driving style clustering algorithm is effective.

In 494,403 training samples, the proportions of aggressive, moderate and conservative driving styles

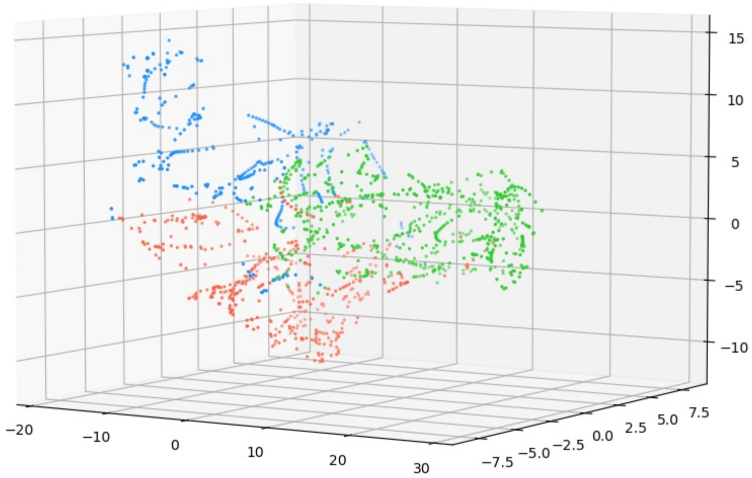


Figure 4. Visualization of the driving style clusters.

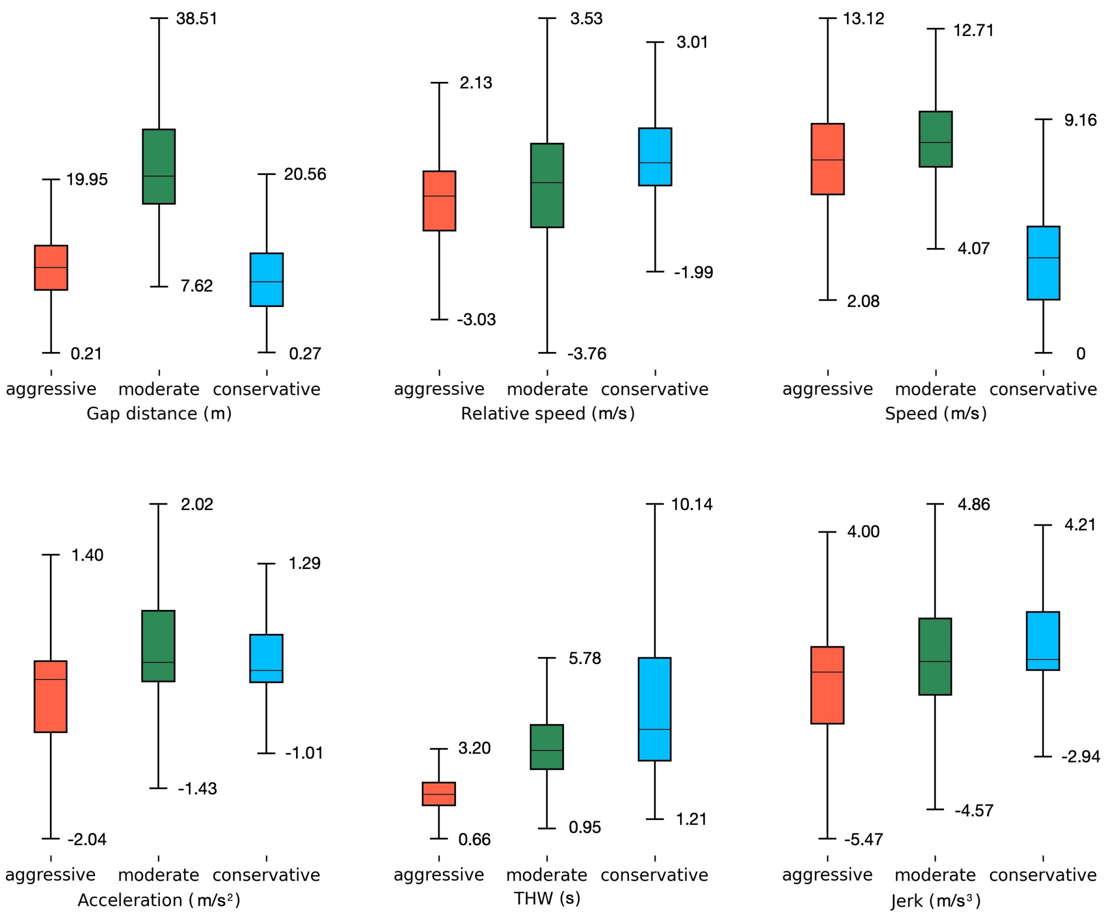
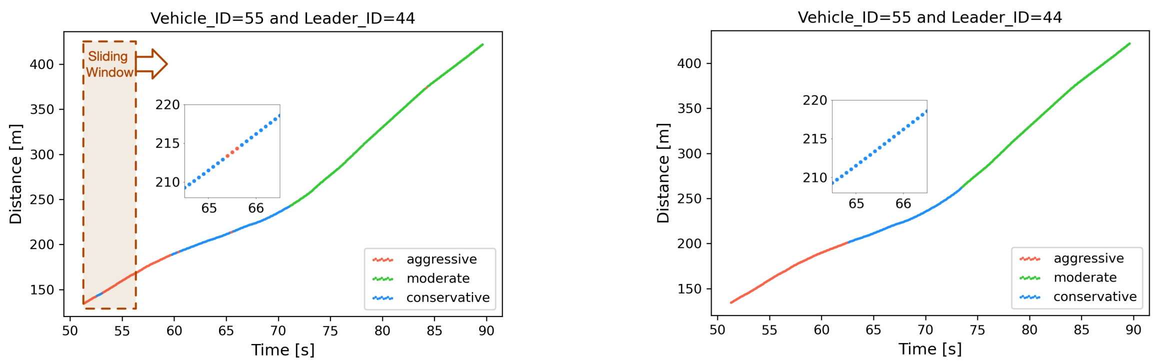


Figure 5. Statistical plot of characteristic variables in terms of different driving styles.

are 39.6, 23.5 and 36.9%, respectively. The statistical analysis is implemented on characteristic variables to illustrate the difference in driving styles. The statistical plot is shown in Figure 5. It can be seen that a distinguished diversity exists in the time headway preferences among different driving styles. The aggressive driving style keeps a much shorter time headway than others, has a broader variation in range of speed and is more likely to brake sharply. Compared to the moderate driving style, it tends to maintain a smaller gap distance. In contrast, the moderate driving style maintains suitable speed and time headway, generally avoiding inappropriate acceleration and deceleration. The conservative driving style occurs mainly when the following gap distance and speed are small, like in jam situations, and it keeps the longest time headway compared to aggressive and moderate driving styles. Moreover, it tends to accelerate or decelerate slightly and smoothly.

4.3. Online driving style recognition

As driving style types can be identified at the timestep level, unrealistic switching of driving styles may occur, as shown in Figure 6(a). This issue is solved with the sliding window technique illustrated above. As the historical information for 50 timesteps (5 s) is proven to be qualified to reflect the memory effect [45–47], t_m is set as 50. Thus, the driving style recognition result is obtained, as presented in Figure 6(b).



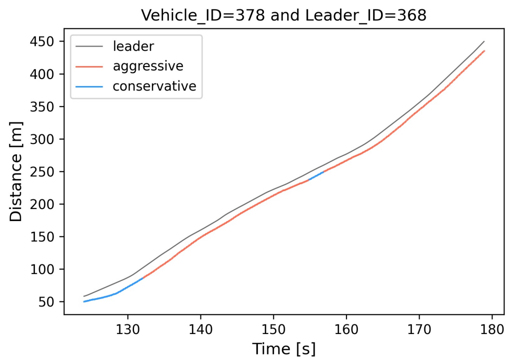
(a) Driving style clustering result

(b) Driving style recognition result

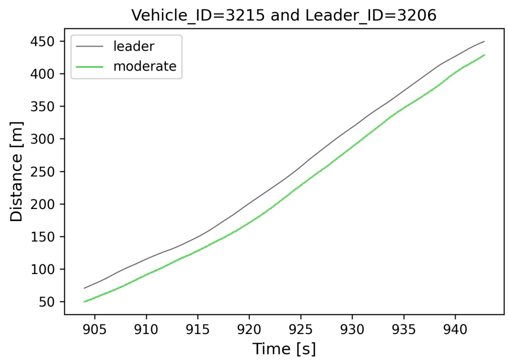
Figure 6. Driving style recognition with sliding window technique.

The test set is processed using the well-trained PCA and k-means combined algorithm, along with the sliding window technique, to observe and analyze driving style recognition results. Figure 7(a)–(c) depicts examples of car-following events dominated by different driving styles. These illustrations highlight the inter-driver differences, where drivers exhibit preferences for various driving styles even under similar traffic conditions. Factors contributing to these differences include the drivers' personalities, skills, travel purposes and other individual characteristics.

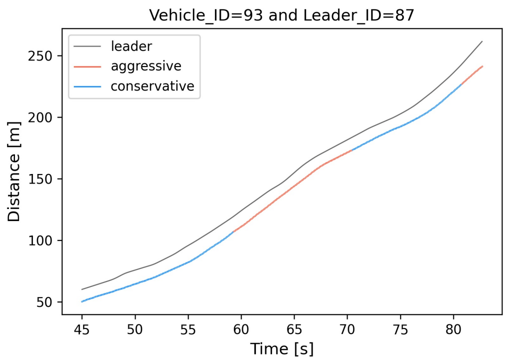
Figure 7(d)–(f) displays randomly selected examples of mixed driving styles in which all three driving style types (aggressive, moderate and conservative) can be observed within a single car-following event. These examples demonstrate the presence of intra-driver differences, where a driver may alter their driving style based on the current traffic conditions. Furthermore, distinct drivers tend to exhibit similar choices when facing comparable situations. For instance, in the three car-following events shown, the following vehicles all adopt a conservative driving style when the leading vehicles deceler-



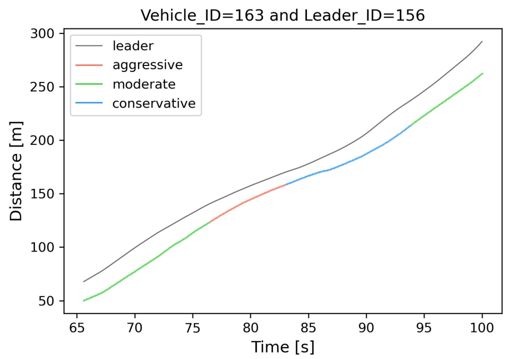
(a) Aggressive driving style dominant



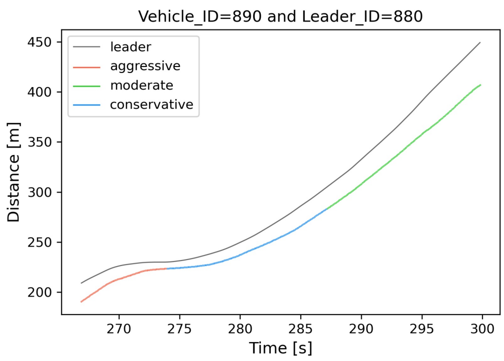
(b) Moderate driving style dominant



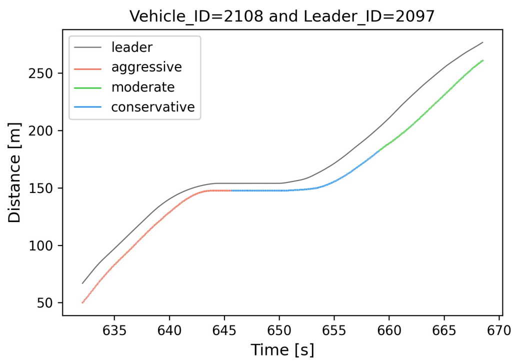
(c) Conservative driving style dominant



(d) Mixed driving styles Example 1



(e) Mixed driving styles Example 2



(f) Mixed driving styles Example 3

Figure 7. Examples of driving style recognition results of car-following events.

ate, prioritizing safety. This observed behavior aligns with the characteristics of conservative driving style discussed earlier. Consequently, the adaptive nature of driving behaviors is apparent, justifying the use of online driving style recognition for human-like car-following modeling.

4.4. Model testing

The model parameter vector θ is calibrated based on the clustered training data, where 70% of samples for each style group are randomly selected as the calibration set, and the remaining samples are used as the validation set. It is acknowledged that the genetic algorithm (GA) [63] is a widely employed calibration method because it can avoid local minima and reach the global optimum with stochastic global search [64]. We conduct the calibration process with Python, and the main settings are presented as follows:

- The optimization objective is to minimize the error between the calculated acceleration ($\hat{\dot{v}}$) and the observed acceleration ($\dot{v}$). The mean squared error is used as the objective function, and the calculation formula is as follows:

$$\text{mse} = \frac{1}{m}\sum_{i=1}^{m}[\dot{v}(i) - \hat{\dot{v}}_n(i)]^2 \tag{4.1}$$

- The bounds of parameters are set referring to Saifuzzaman et al. [64], as displayed in Table 4.
- The GA parameters are total iterations 1000, population size 1000, crossover rate 0.9 and mutation rate 0.0125.

The optimum sets of calibrated parameters of IDM and HIDM are presented in Table 4. The suffixes "un" and "st" represent unstable and stable, respectively.

Table 4. Calibrated parameters.

	type	parameter vector	$\tilde{a}$ (m/s^2)	$\tilde{b}$ (m/s^2)	$\tilde{v}$ (m/s)	t_0 (s)	s_0 (m)
bound	/	/	[0.1,4.0]	[0.1,4.5]	[0.3,41.7]	[0.1,4.0]	[1.0,10.0]
IDM	/	θ	2.02	1.43	22.89	1.40	2.75
	aggressive	θ_{agg}	1.17	3.85	28.04	1.02	2.25
HIDM_un	moderate	θ_{mod}	1.08	2.85	25.38	1.86	2.42
	conservative	θ_{con}	1.42	3.34	17.81	1.34	2.18
	aggressive	θ_{agg}	2.27	2.41	29.14	1.00	2.08
HIDM_st	moderate	θ_{mod}	1.68	1.38	29.06	1.74	3.20
	conservative	θ_{con}	2.41	3.24	26.42	1.35	2.17

In the simulation environment, the predicted trajectory is computed step by step with the iteration of discrete-time car-following process based on the calculated acceleration rate at each timestep, as formulated in Eq (4.2). The mean squared error (MSE) between the simulated trajectory and the observed trajectory is employed as the performance evaluation indicator, as presented in Eq (4.3). A lower MSE reflects a better fit between simulated and observed trajectories and signifies improved performance of the car-following model.

$$\begin{cases} a(t+1) = \dot{v}(\Delta x, v, \Delta v; \theta(t)) \\ v(t+1) = v_n(t) + a_n(t+1)\Delta t \\ x(t+1) = x_n(t) + v_n(t)\Delta t + \frac{1}{2}a_n(t+1)\Delta t^2 \end{cases} \tag{4.2}$$

$$\text{MSE} = \frac{1}{M}\sum_{i=1}^{M}[\dot{x}(i) - \hat{\dot{x}}_n(i)]^2 \tag{4.3}$$

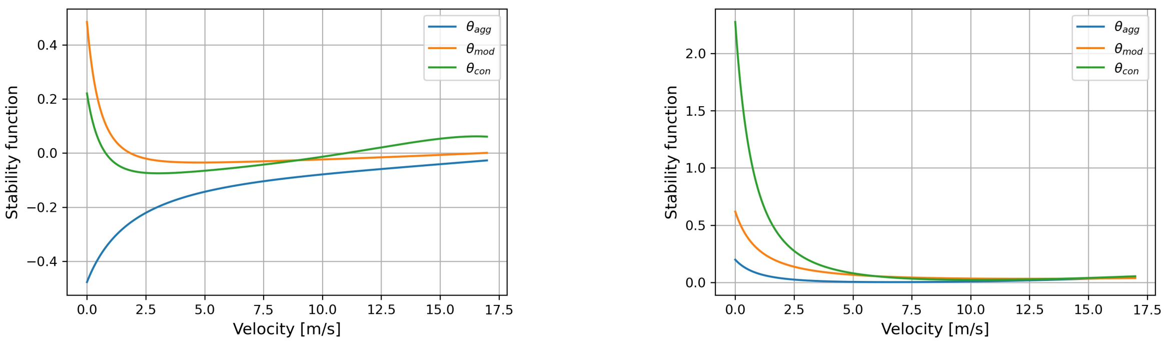
where M is the number of trajectory points. $\dot{x}(i)$ and $\hat{\dot{x}}(i)$ are the observed and simulated locations at the i th timestep, respectively.

To facilitate understanding, the corresponding statistical results are compared in Table 5. IDM is a widely recognized car-following model, providing reliable trajectory reproduction results. However, when compared to IDM, the proposed HIDM demonstrates smaller mean and standard deviation (SD) values, indicating improved performance. Additionally, HIDM's overall performance surpasses that of IDM, as evidenced by the lower values in the percentiles.

Table 5. Statistical results of the performance.

Model	Mean (SD)	Min	Max	Percentile [25%, 50%, 75%]
IDM	26.74 (38.70)	1.21	374.28	[8.28, 14.87, 29.91]
HIDM_un	23.93 (34.19)	0.80	290.49	[6.66, 12.49, 26.79]
HIDM_st	25.85 (36.84)	0.75	377.21	[5.43, 11.86, 28.46]

In accordance with the string stability analysis framework, the stability value relative to equilibrium speed is computed, and the string stability plots are displayed in Figure 8. It is evident that HIDM_st remains stable for any equilibrium speed, as the stability values consistently stay above zero. Notably, it can be observed that adopting a conservative driving style is more stable when the vehicle speed is slow, while employing an aggressive driving style approaches an unstable state, which aligns with real-world scenarios. For HIDM_un, although it has a higher prediction accuracy for the actual trajectory, with an average MSE of 23.93, it does not satisfy string stability and cannot be applied to longitudinal control of autonomous vehicles.

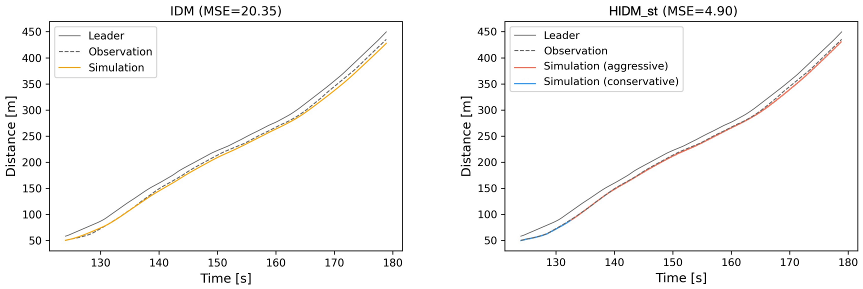


(a) HIDM_un (b) HIDM_st

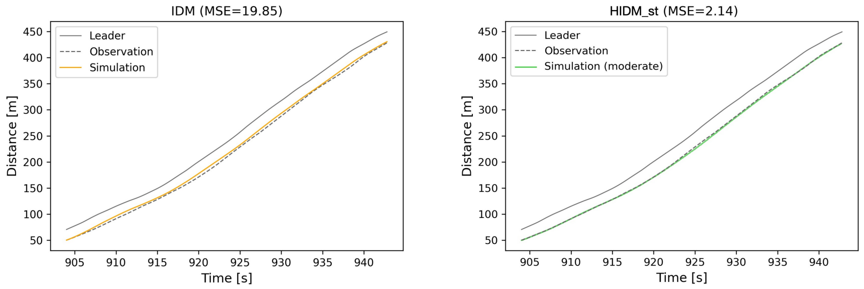
Figure 8. String stability analysis.

To offer a visual examination of the simulation outcomes, we construct time-space diagrams that compare the observed and simulated trajectories. We choose the car-following events depicted in Figure 7 as our examples. Figure 9 presents the reproduced trajectory profiles of four representative patterns of driving style distribution, including aggressive, moderate, conservative and mixed driving styles. The results show that HIDM outperforms IDM in terms of trajectory prediction accuracy. Comparing the results in Figure 9 with the observed driving behaviors in Figure 7, we find that HIDM closely aligned with the observed driving behaviors, demonstrating the model's effectiveness in accurately capturing and representing various driving styles. Moreover, Figure 9(d) showed that the model could reflect intra-driver differences effectively by reproducing individual trajectories of mixed driving styles.

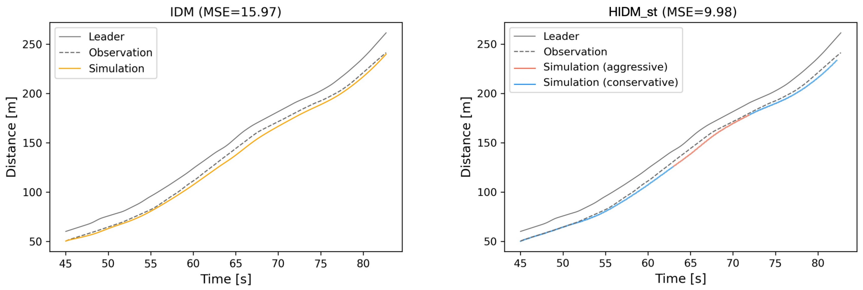
4.5. Platoon simulation



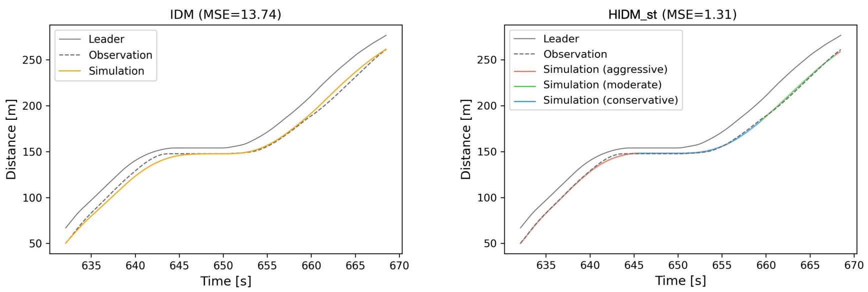
(a) Aggressive driving style dominant (Vehicle_ID=378 and Leader_ID=368)



(b) Moderate driving style dominant (Vehicle_ID=3215 and Leader_ID=3206)



(c) Conservative driving style dominant (Vehicle_ID=93 and Leader_ID=87)



(d) Mixed driving styles (Vehicle_ID=2108 and Leader_ID=2097)

Figure 9. Comparison of models' performances.

From the above simulation analysis, it is clear that HIDM performs well in trajectory prediction.

HIDM_st is suitable for the control system due to its string stability property. However, it appears that HIDM_un has higher simulation accuracy for trajectory reproduction based on the statistical results. To further explore this observation, we conduct platoon simulations with both HIDM_un and HIDM_st.

The platoon simulation is implemented differently than a vehicle pair trajectory simulation. In the pair simulation, the following vehicle is simulated based on the observed trajectory of the leading vehicle. In the platoon simulation, except for the first following vehicle, the other following vehicles run the simulation based on the simulated trajectory of the preceding vehicle. As the simulation error will accumulate and become more exaggerated in the platoon simulation, the string stability of models can be more easily observed.

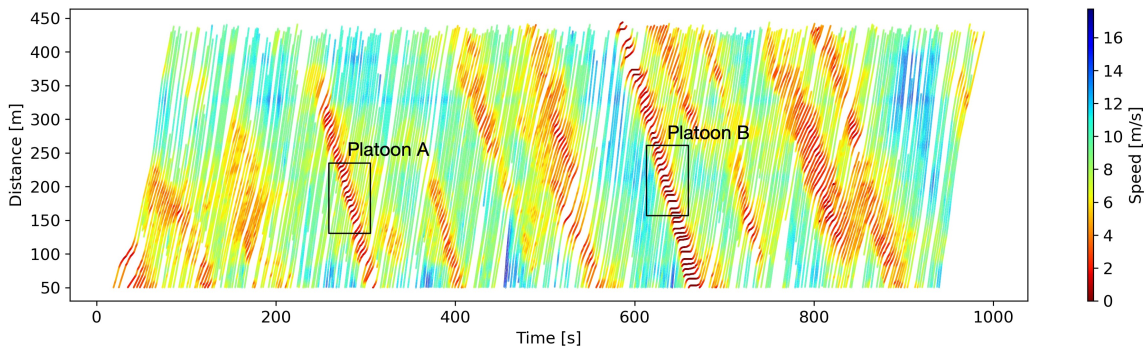
The time-space diagram of test data is plotted in Figure 10(a), and two vehicle platoons are labeled. It shows that the platoons traverse through stop-and-go waves. The simulated trajectories are generated based on the observed data of the leading vehicles (Vehicle 898 for Platoon A and Vehicle 1941 for Platoon B) and the initial states of the following vehicles. The observed and simulated trajectories of the two platoons are presented in Figure 10(b),(c).

Figure 10(a) shows that there are noticeable differences in the behaviors of Platoons A and B. The perturbation wave for Platoon A seems to dissipate slightly, while the oscillation wave for Platoon B propagates upstream to a significant extent. This difference in wave behavior leads to a conclusion that Platoons A and B exhibit comparatively stable and unstable properties, respectively. To further analyze the behavior of the two platoons, the simulation results show that the HIDM_st model performs better for the simulation of Platoon A, while the HIDM_un model is more suitable for Platoon B. These findings indicate that the original trajectory data from human drivers tends to be unstable, which further implies the importance of personalized driver models to account for variations in driving style and behavior.

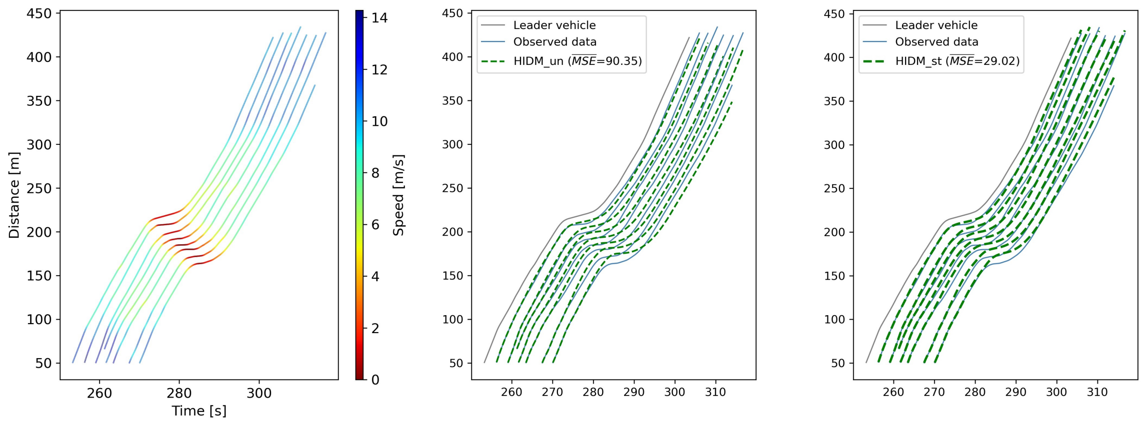
5. Discussion

Our study implements the decision-making process in two steps: we primarily use the k-means algorithm to identify the driving style; then, based on the results from the first step, we employ the genetic algorithm to calibrate the kinematics-based car-following model. In recent years, advanced optimization algorithms, such as customized heuristics and metaheuristics algorithms [65–67] and multi-objective optimization algorithms [68–70], have gained widespread attention for their effectiveness in solving complex decision-making problems. They have been employed as solution approaches across various fields, demonstrating their ability to manage multiple objectives and constraints while adapting to dynamic and uncertain environments.

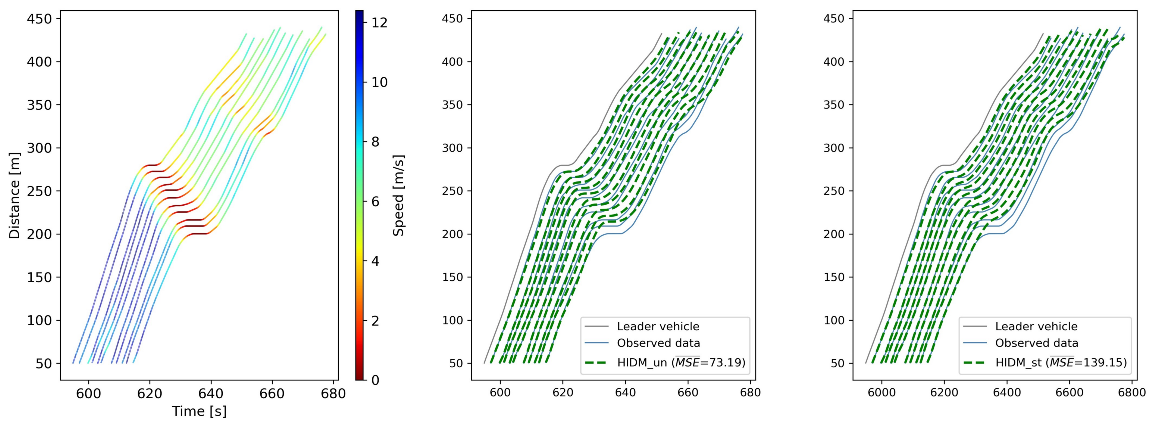
Advanced optimization algorithms play a crucial role in enhancing the performance of car-following models, which are fundamental to autonomous driving. These algorithms tackle complex optimization problems in calibration, control and motion planning. For example, studies have employed global optimization algorithms for calibrating car-following model parameters [71], particle swarm optimization (PSO) for tuning model predictive control (MPC) weights [72] and accelerated particle swarm optimization (APSO) for motion planning in MPC formulations [73]. In future research, it would be valuable to compare the performance of the approach proposed in our study with advanced optimization algorithms, in order to assess the potential benefits and improvements that these algorithms may offer. Through a comparative analysis that considers accuracy, adaptability and computational effi-



(a) The observed trajectories of Platoon A and Platoon B



(b) Platoon A following Vehicle 898



(c) Platoon B following Vehicle 1941

Figure 10. Platoon simulation.

ciency, researchers could gain a deeper understanding of the strengths and weaknesses inherent to each approach. Such a comparison could ultimately facilitate the identification of potential enhancements in car-following models and autonomous driving technologies, paving the way for more effective and safer driving solutions.

6. Conclusions

Human-like car-following modeling helps improve the performance of driving automation. This study aims to explore the variation characteristic of driving style with a high-fidelity human-driven dataset and to establish the car-following model for driving style adaption in real-time. The proposed HIDM is calibrated with clustered training data and compared with calibrated IDM on trajectory simulation. The string stability of HIDM is analyzed and further validated in platoon simulation. The main findings are concluded as follows:

- Trajectory samples are clustered into three types (aggressive, moderate and conservative) in terms of driving style. The driving style types are visualized with a dimensionality reduction technique, showing an explicit distinction.
- The driving style recognition results of car-following events reveal not only heterogeneity, in that drivers prefer different driving styles because of individual-related factors, but also homogeneity, in that they may have common choices in similar situations.
- The driving style recognition results show that most drivers do not always maintain one driving style. There are intra-driver differences. In other words, a driver can change one's driving style with the influence of related factors such as traffic conditions.
- Compared with the observed trajectory, the simulated trajectory with HIDM preserves the actual driving styles, which means that HIDM can capture the driving style characteristics in car-following events.
- The stability analysis and platoon simulation reveal the presence of instability in the traffic flow of human-driven vehicles. HIDM_st meets the string stability criteria for any equilibrium speed and can be effectively applied to the longitudinal control of autonomous vehicles.

Taking a comprehensive view of this research, it is worth mentioning that certain aspects may require further examination and exploration in future investigations, as they are not fully addressed within the scope of this study. Although the combination of PCA and k-means clustering offers a balance between simplicity, effectiveness and interoperability, there is potential for exploring alternative approaches in future research to further enhance the performance of the driving style recognition and modeling framework. Furthermore, the accuracy of these recognition results remains unassessed due to the lack of a well-defined baseline for comparison. Future research endeavors may consider conducting localized car-following experiments to further validate the driving style recognition outcomes.

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Conflict of interest

The authors declare there are no conflicts of interest.

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