Factors in Modeling the Car-Following Behavior

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Car-following behavior is the result of the interaction of various elements in the specific driver-vehicle-environment aggregation. Under the intelligent and connected condition, the information perception ability of vehicles has been significantly enhanced, and abundant information about the driver-vehicle-environment factors can be obtained and utilized to study car-following behavior. Therefore, it is necessary to comprehensively take into account the driver-vehicle-environment factors when modeling car-following behavior under intelligent and connected conditions.

traffic flow theory car-following model traffic information

1. Introduction

Car following refers to the vehicle behavior of maintaining the current lane and following its preceding vehicle(s). Modeling car-following behavior involves the longitudinal motion of vehicles in the lane, which is one of the core parts of traffic flow theory. The research on car-following behavior goes back nearly 70 years and covers hundreds of models; it is based on various theories, and different perspectives have been constructed in the developing process. According to the modeling idea, these models can be divided into six types: stimulus-response models, safety distance models, physiology-psychology models, artificial intelligence models, optimal velocity models, and intelligent driving models [1][2][3][4][5]. Among them, the representative models' developing process is shown in **Figure 1**.

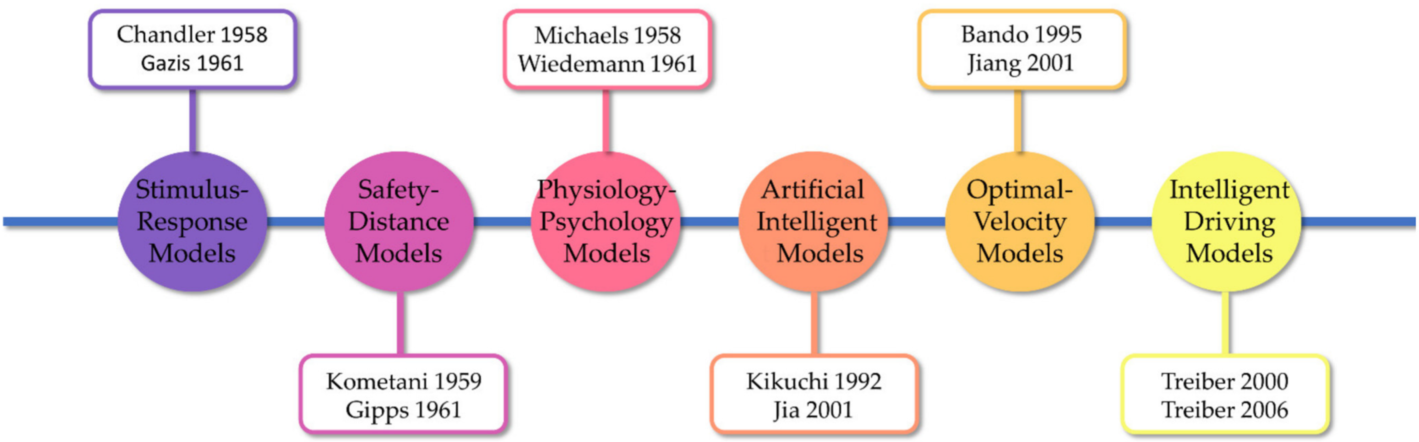

Figure 1. Development process of traditional car-following models.

With the deepening of research, it has been found that the vehicle and its driver, as a whole unit, will present different characteristics of car-following behavior in various driver-vehicle-environment aggregations. It is necessary to carry out in-depth exploration of car-following behavior as affected by various driver, vehicle, and environment factors and to further study the traffic flow under different conditions. On the other side, intelligent and connected technology has been rapidly developing in the last few years. Supported by intelligent and connected technology, the transportation system is expected to be safer, more efficient, and more environmentally friendly, which is vital to the sustainability of the society. With the help of the applications of intelligent and connected technologies, represented by vehicle-to-everything (V2X) technology, the vehicle's information perception ability has been significantly enhanced. Based on this, abundant information about factors in the driver-vehicle-environment aggregation can be obtained and utilized by the vehicle–driver unit in the car-following process. Thus, the comprehensive consideration of driver, vehicle, and environment factors is indispensable when modeling car-following behavior under the intelligent and connected condition.

2. Factors in Modeling the Car-Following Behavior

2.1. Driver

The impact of driver attributes cannot be ignored when modeling car-following behavior. However, these impacts are not comprehensively considered in the traditional car-following models. In these models, drivers in the system are assumed to be homogeneous, which is inconsistent with reality. Due to the differences in the driving experience, mental state, character, and other sociological characteristics, drivers will present different car-following characteristics. On the one hand, the car-following behavior of various drivers may be different under the same conditions (this is defined as "external heterogeneity"). On the other hand, the car-following behavior of the same driver could be different under the same conditions at different times (this is defined as "internal heterogeneity").

2.1.1. External Heterogeneity

External heterogeneity describes the differences in the car-following behavior of different drivers. There are significant differences in car-following behavior among various drivers. These differences not only affect the motion state of vehicles at the micro level but also are the main factor affecting the nonlinear characteristics of traffic flow at the macro level [6]. These effects can be detected in the field data. According to this, many scholars have analyzed drivers' external heterogeneity from the empirical analysis perspective. Brackstone et al. discussed the impacts of drivers' characteristics on time headway in the car-following state [7]. The results reveal that the correlation between headway and driver age is the strongest one when following at high velocity. Ossen and Hoogendoorn first recognized drivers' external heterogeneity along with its influence on micro and macro levels as pointed out in [6] from field data [8]. Later, other scholars analyzed and discussed the impact of driver heterogeneity on car-following behavior and even traffic flow operation characteristics based on different datasets. In recent years, with the development of mobile and high-performance computing technology, real vehicle driving experimental systems based on multi-sensor arrays and high-fidelity virtual driving systems are increasingly used in the research on car-following behavior, especially in the exploration of heterogeneity.

Doroudgar et al. [9] analyzed the differences in car-following behavior between young and older drivers in terms of reaction time based on virtual driving experiments. The results suggest that the older drivers have a longer reaction time, have poorer ability to maintain headway, and maintain lower velocity (the distribution of velocity is more concentrated). Qi et al. [10] discussed the differences in discomfort degree in various scenarios between drivers using actual vehicle driving experiments and proposed a recognition model for this discomfort degree. The results reveal that the discomfort degree can be employed as the feature to identify the driver. Based on the extended curve Full Velocity Difference (FVD) model [11], An et al. [12] further introduced a reaction time item with a delay parameter to describe the differences in reacting to the same situation among drivers with different driving experiences and constructed a curve FVD model with consideration of driver heterogeneity. Later, the differences in the car-following characteristics of drivers with diverse cultural backgrounds were discussed by Cheng et al. [13] based on virtual driving experiments.

2.1.2. Internal Heterogeneity

There are significant differences in car-following behavior among different drivers, which is defined as external heterogeneity. The car-following characteristics of the same driver under various conditions or even under the same condition will be different due to psychology, physiology, or physical influence, which is defined as internal heterogeneity. To explore the car-following behavior with consideration of internal heterogeneity, Hamdar et al. [14] incorporated the internal heterogeneity in the aspect of collision risk cognition and proposed a prospect theory-based car-following model. Zhu et al. [15] introduced two delay items, proposed an extended Newell model, and discussed the impacts of changes in the delay of the same driver on car-following behavior and traffic flow. Yu et al. [16] further discussed the impacts of drivers' delay on the propagation and evolution of density waves. Utilizing the field data collected from a highway in Holland, Wang et al. [17] re-calibrated the Helly, Gipps, and ID models and, based on this, discussed the internal heterogeneity in reaction intensity during acceleration/deceleration. Under the condition of restricting lane-changing, traffic flow turbulence still occurs. Laval et al. [18] assumed that this phenomenon may be caused by the internal heterogeneity in the desired velocity; the authors added noise of the desired velocity into the Newell model and successfully reproduced the phenomenon. Saifuzzaman et al. [19] utilized the Task Capability Interface (TCI) to describe the correlation between the driving task requirements and driving ability, further incorporated this TCI-based model into the Gipps and ID models, and calibrated these extended models with virtual driving data. Later, Pekkanen et al. [20] confirmed that the TCI-based model can express the driver's internal heterogeneity using virtual driving experiments. Based on the statistical analysis of car-following trajectory data collected from a highway, Huang et al. [21] identified the internal heterogeneity in car-following behavior. Based on this, Huang et al. [22] proposed an extended two-dimension ID model. Lindorfer et al. incorporated the time-varying reaction time affected by various scenarios into the ID and HD models and further modeled the errors in car-following behavior. The results suggest that there are errors in the driver's cognition of headway, relative velocity, and acceleration, and these errors are not constant.

2.2. Vehicle

The vehicle is the specific tool for the driver to execute their car-following behavior. Due to this, the physical and dynamic characteristics of vehicles will affect the driver's car-following behavior. First, when deciding which car-following behavior to take, the driver will consider whether the physical and dynamic characteristics of the vehicle he/she drives can meet the requirements of the car-following behavior he/she wants to take and, according to this, adjust his/her car-following behavior. For instance, when driving a heavy vehicle, considering the acceleration and deceleration performance, the driver will adopt relatively low speed and acceleration and relatively large headway to match the performance of the vehicle he/she is driving. Second, in addition to the vehicles driven, the physical and dynamic characteristics of other vehicles, especially the preceding vehicle, will also affect the driver's car-following behavior. For example, when following a heavy vehicle rather than a normal vehicle, the driver will adopt relatively large headway and low speed. Third, with the development of intelligent vehicles, assisted driving, including automatic driving systems such as Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC), is applied. Autonomous lane-keeping and car-following have been realized. Compared with the human driver, the vehicle will show different car-following characteristics when controlled by these automatic controllers.

2.2.1. Types

Dividing vehicles with different types into various car-following combinations

It has been widely acknowledged in the field of traffic flow theory that when there are multiple types of vehicles driving in the same road segment, especially when there are heavy vehicles, the operating and stability characteristics of traffic flow at both the micro and macro level will be significantly affected. In the previous studies on car-following behavior with consideration of impacts of vehicle types, the approach of dividing the mixed flow into various car-following combinations was widely employed. For instance, when the subject vehicle is a car, and its preceding vehicle is a truck, this car-following combination is Truck-Car (i.e., T-C). Similarly, there are C-T, H-C (Heavy-Car), C-H, B-C (Bus-Car), C-B, B-H, and so on. This approach, dividing vehicles with different types into various car-following combinations, was first utilized in the research on car-following behavior by Peeta et al. [23] studying differences in car-following behavior of the subject vehicle between the H-C and C-C. The results reveal that the driver tends to take larger headway when the preceding vehicle is a heavy one rather than a car. After this, many researchers explored the car-following characteristics with consideration of various combinations. In the research on driver's car-following characteristics in different combinations, Aghabayk et al. made a significant contribution.

Direct consideration of vehicle type impacts

In addition to the abovementioned approach (dividing vehicles with different types into various car-following combinations), there is another approach widely used to explore car-following behavior with consideration of vehicle type. In this approach, the car is set as the normal vehicle, and the truck, bus, heavy vehicle, and other types of vehicles are set as the non-normal vehicle. Based on this, the car-following model can be constructed by incorporating the dynamic and behavior characteristics of each type of vehicle. For instance, the specific power and deceleration ability of heavy vehicles are relatively lower than that of normal vehicles, and these dynamic characteristics will lead to differences in car-following and other driving behaviors. Considering this, Li et al. [24] proposed an improved car-following model based on the speed-dependent control gains, and the heavy vehicle's dynamic characteristics were incorporated in this model. When the car-following model is regarded as an algorithm to control the longitudinal motion of the vehicle, the car-following process can be regarded as a typical Cyber Physical System (CPS).

2.2.2. Sorts

With the development of intelligent vehicles, a new sort of vehicles equipped with automatic controllers is now part of the traffic system. Up to now, the car-following characteristics of automatic controllers have been significantly different from that of human drivers. Thus, the vehicles equipped with automatic controllers should be regarded as a new sort, to distinguish them from manual vehicles (MVs) when modeling car-following behavior. Recently, the research on traffic flow composed of this new sort of vehicles and MVs has become the frontier and a hot topic in the field of traffic flow theory. Zhu et al. [25] employed basic and extended OV models to respectively describe the car-following behavior of the manual and new sort of vehicles and analyzed the impacts of sensitivity, the smooth factor, and new vehicles' penetration rate on traffic flow. The results suggest that the traffic flow volume is positively related to the above three parameters before the critical point and negatively related to them after this point. Based on the model proposed in [26] to describe the car-following behavior of vehicles equipped with CACC systems, Qin et al. [27][28] derived the platoon stability of the new sort of vehicles and MVs utilizing the transfer function method. The results suggest that by altering the feedback coefficient, the platoon may reach the ideal stability condition, that is, the platoon can maintain a stable state under any condition. Seraj et al. [29] respectively employed the basic FVD model and an extended FVD model to describe the car-following behavior of connected automatic vehicles (CAVs) and MVs to construct a control strategy for the mixed platoon. The results reveal that adopting a small headway for each vehicle and a large total length for the platoon can improve the efficiency but damage the safety.

2.3. Environment

The research on car-following behavior cannot ignore the specific environment in which the object vehicle is located. There are differences in the car-following behavior when the vehicle is in various kinds of environments. In the traditional car-following models, the environmental factors are assumed to be ideal. To be specific, the road and weather conditions are assumed to be consistently good, and slope, curvature, or snow do not exist. These unrealistic assumptions lead to those models showing poor performance when used to describe the car-following behavior in realistic, complex traffic scenarios.

2.3.1. Road

Road condition

Different from the traffic conditions that indicate traffic congestion on the road, road conditions are the technical conditions of the main body, surface, structure, and accessories of the road. In traffic flow theory, a good road condition is regarded as the normal road condition. According to driving experiences, when the road condition deviates from the normal condition, the car-following behavior will be affected and show different characteristics. Therefore, in the research on car-following behavior, the road condition refers to the damage to road surface or other components.

There are impacts of road condition on traffic flow at both the micro and macro levels.

(1) Micro level. The vehicle's acceleration/deceleration/velocity/headway/energy consumption/exhaust emissions in the starting, driving, and braking process are all affected by the road conditions. Specifically, the lasting time will enlarge, and the velocity along with acceleration/deceleration will decline in the starting and braking process. There will be a disturbance in the velocity and headway in the driving process, which will cause an increase of energy consumption and exhaust emissions.

(2) Macro level. The stability of traffic flow will be enhanced, and the shock wave will be alleviated when the road condition is good. It is noteworthy that there are negative impacts of good road condition on stability when the traffic flow is evaluated for the stop-and-go state.

Slope

On a road with slope, there will be a tendency for the vehicle to move towards a lower position due to gravity, and the driver will take measures to counteract this tendency to maintain a safe and desired driving state. To be specific, the vehicle needs to output more power to reach the same acceleration when going uphill than on a flat road, and the vehicle needs to output more brake force to reach the same deceleration when going downhill. These impacts of gravity will also make the driver correspondingly adjust the headway in the car-following process. Li et al. [30] first analyzed the maximum velocity and safety headway when car-following on roads with different slopes. In this work, Li et al. summarized a general expression of the optimal velocity function to describe the relationship between the optimal velocity function and position, slope, and safety headway. Based on this, Li et al. [31] proposed an extended OV model and analyzed the traffic flow utilizing numerical simulation. Different from the approaches that Li used to form the general expression of the optimal velocity function by analyzing the driver's behavior characteristics, Komada et al. [32] proposed an extended OV model based on the force analysis of vehicles on roads with slope.

The slope OV model has a similar structure to the basic OV model and two optimal velocity functions, which are suitable for the uphill and downhill. Based on this slope OV model, Komada et al. analyzed traffic flow with the help of numerical simulation and detected the congestion position on various slopes by adjusting the traffic flow density. However, theoretical analysis of the traffic flow on roads with slope is still absent. Aiming at this, Zhu and Yu [33] derived the neutral stability condition and the nonlinear characteristics near the critical point of the traffic flow based on Komada's model. During the same period, Zhu and Yu [34] derived the Korteweg-de-Vries (KdV) equation and the solitary solutions in the metastable region based on Komada's model. Soon after, Zhu [35] combined Komada's model and the energy consumption and exhaust emission model proposed by Li et al. [31] to construct an energy consumption and exhaust emission estimation model for vehicles on roads with slope. Based on [33] and the energy consumption model for electric vehicles [36], Yang et al. [37] proposed an improved energy consumption model with consideration of the impacts of slopes and the kinetic energy recovery system. Two nondimensional parameters were introduced, which represent the impacts of fog on a driver's misjudgment of the headway and the corresponding reduction of velocity, by Tan et al. into Komada's model to form an extended model and to analyze car-following behavior as affected by the fog and slope [38]. Based on [33], Zhang et al. [39] further considered the two relative velocities (forward and backward), constructed an extended slope OV model, and derived the corresponding macro flow model.

Curve

The curve refers to the section with a curvature on the road. When the vehicle is driving on a curve, on the one hand, the driver needs to adjust the direction to control the vehicle along the road curve; on the other hand, the velocity cannot be high due to the limitation of centrifugal force. The above-mentioned two points lead to the fact that the driving characteristics of vehicles on curves are different from those on straight roads.

Gyroidal road

The gyroidal road is a section with both slope and curvature. The curve and slope of roads in the actual traffic system are not independent of each other, and quite a number of roads are both curved and sloped. A typical gyroidal road is a ramp to elevated roads. However, there is no consideration of the gyroidal road, that is, the curve and slope are not considered at the same time. To address this, Zhu et al. [40] introduced the maximum angular velocity of the gyroidal road, velocity correction due to gradient, and the safety headway affected by slope to modify the optimal velocity function and, based on this, proposed an extended gyroidal OV model. The impacts of the gyroidal road were incorporated into the FVD model by Meng et al. [41], and they derived the stability conditions of traffic flow utilizing control theory. Considering that the H∞ norm can describe the traffic congestion with open boundary conditions and the OV model [42][43], Zhai et al. [44] proposed a delay feedback control method based on the extended gyroidal OV model constructed in [40] and discussed the impacts of controller gain coefficient and delay time on traffic flow on gyroidal roads under the Hulwitz criterion.

2.3.2. Weather

In addition to the road conditions, there are significant impacts of weather on car-following behavior. Good weather is generally regarded as normal weather in the research on car-following behavior. When the weather gets worse, it will increasingly affect the car-following behavior. The impacts of bad weather on driving behavior are significant and widely acknowledged. Because of this, traffic managers around the world will send alerts to drivers when they detect bad weather. The previous norm organized weather according to type, such as rain, snow, and fog. In fact, no matter what type of weather, its impacts on driving behavior can be divided into two aspects: visibility and adhesion. Compared with good weather, the presence of liquid and solid particles in the air in the rain, snow, fog, and other weather will lead to the decline of visibility, which will affect the driver's perception of traffic conditions and then affect his/her car-following and other driving behaviors.

3. Integration of Machine Learning in Car-Following Behavior Modeling

With the advancement of computational intelligence, the integration of machine learning (ML) techniques into car-following behavior modeling has emerged as a promising avenue to address the inherent complexity and variability in driver-vehicle-environment interactions. Traditional rule-based models often rely on pre-defined mathematical functions, which limit their adaptability to dynamic traffic conditions and heterogeneous driver profiles. In contrast, ML algorithms can extract nonlinear patterns from large-scale driving datasets, enabling the construction of data-driven car-following models that account for individual differences, contextual factors, and real-time variability.

Supervised learning methods such as random forests, support vector machines, and deep neural networks have been successfully applied to predict longitudinal vehicle movements based on sensor data, traffic states, and driver characteristics. Recurrent neural networks (RNNs), especially long short-term memory (LSTM) models, offer additional advantages by capturing temporal dependencies in car-following behavior, making them suitable for modeling sequential driving decisions. Furthermore, unsupervised techniques like clustering can help classify driving styles, contributing to the personalization of car-following strategies in intelligent vehicles.

The integration of ML not only enhances predictive accuracy but also facilitates the development of adaptive cruise control systems and cooperative vehicle platoons that respond intelligently to varying traffic scenarios. However, the black-box nature of many ML models poses challenges regarding interpretability and safety validation. Therefore, hybrid approaches that combine interpretable rule-based logic with data-driven learning are gaining attention for their balance between performance and transparency.

As vehicle connectivity and automation progress, the synergy between machine learning and traditional traffic flow theory is expected to play a pivotal role in the next generation of car-following models, enabling more resilient, safe, and efficient transportation systems.

4. Conclusions

There are differences in the car-following behavior when the vehicle is in various driver-vehicle-environment aggregations, which suggests that it is difficult to use one model to comprehensively and precisely describe the car-following behavior of a vehicle with enhanced information perception ability. Generally speaking, (i) the reality that the car-following behavior is comprehensively affected by various driver-vehicle-environment factors has not been adequately considered, and (ii) the processing approaches of impacts of driver, vehicle, or environment on car-following behaviors were relatively simple in previous studies. Therefore, the comprehensive consideration of driver, vehicle, and environmental factors from a global perspective, fully incorporating the characteristics of various factors' influence, the evolution of modeling and evaluation methods, and the construction of the new generation datasets are the more urgent needs for future works.

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