

Research Article

A New Car-Following Model with Consideration of Dynamic Safety Distance

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Received 19 July 2018; Revised 30 October 2018; Accepted 5 November 2018; Published 12 November 2018

Academic Editor: Giancarlo Consolo

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In the traditional optimal velocity model, safe distance is usually a constant, which, however, is not representative of actual traffic conditions. This paper attempts to study the impact of dynamic safety distance on vehicular stream through a car-following model. Firstly, a new car-following model is proposed, in which the traditional safety distance is replaced by a dynamic term. Then, the phase diagram in the headway, speed, and sensitivity spaces is given to illustrate the impact of a variable safe distance on traffic flow. Finally, numerical methods are conducted to examine the performance of the proposed model with regard to two aspects: compared with the optimal velocity model, the new model can suppress traffic congestion effectively and, for different safety distances, the dynamic safety distance can improve the stability of vehicular stream. Simulation results suggest that the new model is able to enhance traffic flow stability.

1. Introduction

In order to explore congestion mechanisms, researchers have developed several excellent traffic flow models from different perspectives [1–18]. The car-following model, first proposed by Pipes [5], is a kind of microscopic traffic flow model. The idea behind it is that drivers adjust their velocity according to the space headway between their own vehicle and the preceding vehicle. Based on this idea, different types of car-following models were proposed to investigate the characteristic features of traffic flow. Bando et al. proposed an optimal velocity model (OVM) that can reproduce various traffic phenomena, such as phase transitions and stop-and-go congestion patterns [6]. The optimal velocity model attracted extensive attention due to its simplicity and accessibility.

Based on the OVM, various improvements have been put forward to explore the nature of traffic congestion. Some researchers enhanced traffic flow stability by considering different space headway values in intelligent transportation systems (ITS). Nagatani extended the OVM to improve the stability of traffic flow with the help of headway information from the following car [7]. Using headway information from

multiple preceding vehicles, Lenz extended the OVM by incorporating multivehicle interaction [8]. The impact of multianticipative driving behavior has been analyzed using analytical methods and numerical simulations. Based on the ITS approach, Ge et al. proposed another multianticipative OVM [9]. By using linear stability analysis and nonlinear analysis, it was found that the model had a stabilizing effect on traffic flow. In order to make the OVM suitable for cooperative driving control systems, Hasebe et al. developed an extended OVM by using arbitrary car position information throughout the traffic system [10].

Apart from headway, the velocity information from downstream vehicles also plays a significant role in the stability of traffic flow. Considering the negative velocity difference effect, Helbing and Benno Tilch proposed a generalized force model (GFM) [11]. Simulation results suggested that the GFM is more consistent with real traffic conditions than the OVM. Jiang et al. constructed a full velocity difference (FVD) car-following model, which was more effective in describing traffic flow [12]. The corresponding analytical and numerical analysis is presented in detail. Liu et al. proposed a new car-following model that took into consideration the velocity

difference between the current speed and the historical speed of the leading car [13].

OVM improvements have also originated through different approaches, such as velocity fluctuation of the preceding car [14, 15] or multiple preceding cars' velocity fluctuation feedback [16]. Traffic safety, another important topic, was tackled by Tang et al., who developed traffic flow models to explore the impacts of vehicle's safety distances (front and back) on the vehicle safety during the starting process. They also studied other traffic-related problems such as emissions and vehicle communications [17, 18]. Unfortunately, all the above car-following models consider the safety distance to be a constant, which does not correspond to real traffic flow.

In real-world driving, drivers rely on their perception of safety headway. This safety headway changes as the speeds of the current vehicle and the preceding vehicle vary, generally in a direct manner. For example, when a car runs at a speed of 100 km/h, the safety distance should be 100 meters, while, at 50 km/h, a safety distance of 50 meters should be maintained. The constant safety distance in the OV function should be replaced by a dynamic safety distance (DSD). In this paper, we propose a new definition of the dynamic safety distance in OV function. Then, a new car-following model is explored, which takes into account the DSD. The influence of variable safety headway on traffic flow is also studied. This manuscript is organized as follows: an improved car-following model accounting for the DSD is proposed in Section 2; in Section 3, numerical simulations are conducted to explore the impact of DSD on traffic flow; conclusions and future works are given in Section 4.

2. Car-Following Models

2.1. Optimal Velocity Model. The optimal velocity (OV) model was proposed by Bando in 1995, with the following mathematical description:

$$\frac{dv_n}{dt} = \alpha (V(\Delta x_n) - v_n), \quad (1)$$

where α , corresponding to the driver's relaxation time, is a sensitivity coefficient. v_n is the velocity of vehicle n . Δx_n is the distance between the current car and the leading car. $V(\cdot)$ is the optimal velocity, which is upper-bounded monotonically decreasing.

$$V(\Delta x_n) = \frac{v_{max}}{2} (\tanh(\Delta x - x_c) + \tanh(x_c)), \quad (2)$$

where x_c is the safety distance of vehicle n .

2.2. Dynamic Safety Distance Model. In order to obtain a more effective car-following model to describe real traffic, we propose a new definition of safety distance. The safety distance can be denoted by the safety time headway multiplied by instant velocity, i.e., $x_c = T_s \cdot v_n$. The corresponding OV function can be rewritten as

$$V(\Delta x_n) = \frac{v_{max}}{2} (\tanh(\Delta x_n - T_s v_n) + \tanh(T_s v_n)), \quad (3)$$

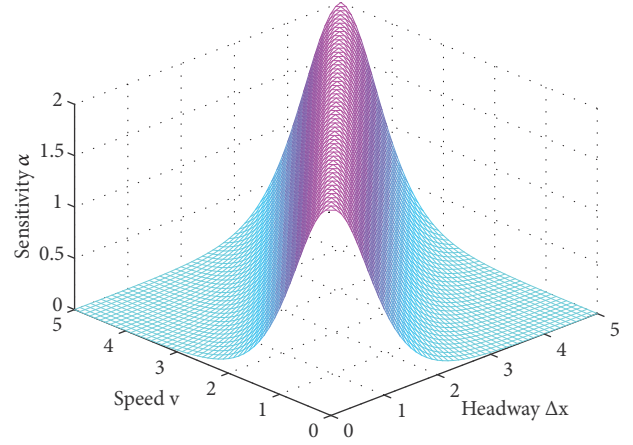


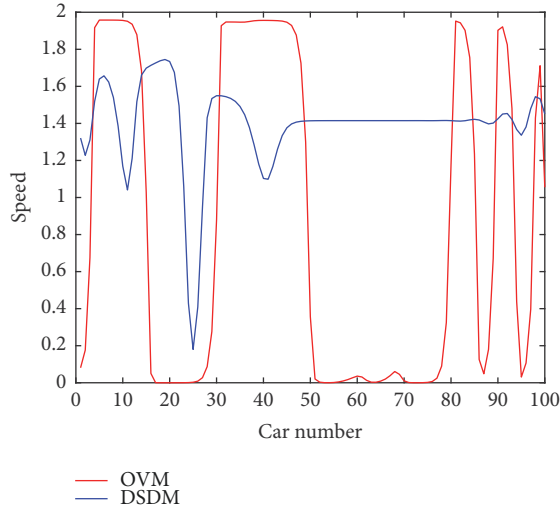
FIGURE 1: Phase diagram in the headway-speed-sensitivity space ($v_{max} = 2.0$).

where T_s denotes the safety time headway, while $T_s v_n$ is the new safety distance of vehicle n . Since the velocity v_n varies with the time t , the original constant-distance equation now becomes dynamic (i.e., (3)). In the following, the OVM with a dynamic safety distance optimal velocity function will be called the dynamic safety distance model (DSDM).

Generally, traffic flow includes three states: the stable state, the unstable state, and the metastate. This paper mainly investigates the stable and unstable states. The parameter space associated with the sensitivity α , speed v , and headway Δx is shown in Figure 1. The whole space is divided into two sections: the stable space and the unstable space. Under the surface, traffic flow is in the stable state, while the volume above the surface corresponds to the unstable state. A small headway (i.e., high density) with a large speed denotes that the traffic flow lies in the unstable state. In this state, headway is less than the safety distance, so drivers will need to decelerate to maintain a safety headway with the front car and avoid collision. In the case of slow speed with large headway (low density), the traffic flow is also in the unstable state, as in this region the driver usually accelerates to follow the car ahead due to the large headway. Figure 1 shows that there is almost no stable space between two regions. For each Δx , there is a unique speed that makes sensitivity α reach the critical point, and, conversely, for every Δx , the critical point is always obtained using a unique speed; all these points form a critical line. When the sensitivity coefficient α is less than a critical value, small disturbances will be amplified into a congested flow, while when α is larger than that critical value, any disturbance will be absorbed and the traffic flow will be restored to its stable state.

3. Numerical Simulation

In this section, numerical simulations are carried out to investigate the impact of variable distance on the dynamics of the traffic system. We first present a comparison between the DSDM and the OVM. The simulation parameters were set as follows: sensitivity (α) was set to 0.5 and 0.8, respectively,

FIGURE 2: Speed profiles for $\alpha = 0.5$, $T_s = 1$ at $t = 300$ s.

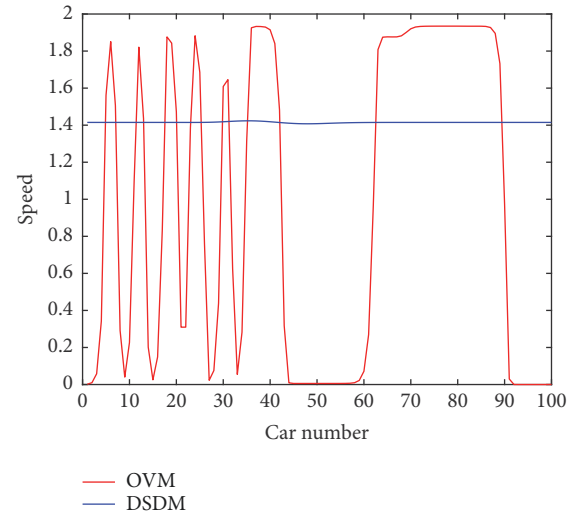
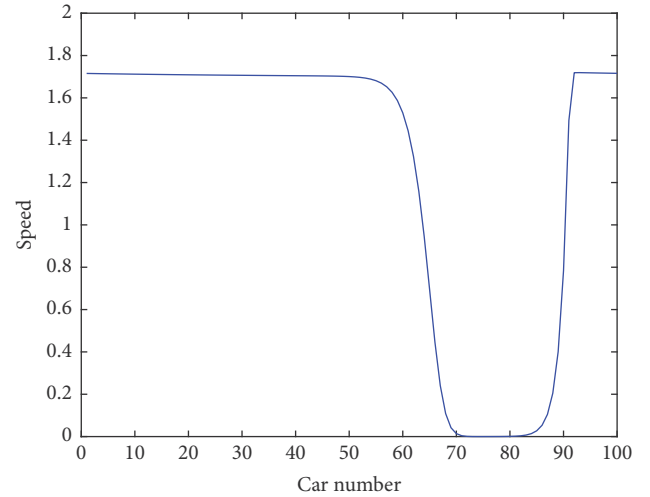
while the safety time headway T_s was set equal to 1 in the DSDM.

We then add a perturbation to the OVM. The evolution of the perturbation at time $t = 300$ is shown in Figure 2. As shown the figure, some vehicles' speed is equal to zero, which means these vehicles cannot move at time $t = 300$, while some vehicles are moving at maximum speed. This is indicative of a stop-and-go traffic pattern. Under the same initial conditions, the simulation results obtained using the DSDM are considerably different from those of the OVM. Although there are some vehicles running at low speed, the number of these vehicles is very small, while there are no stopped vehicles. Accordingly, the maximum speed in DSDM is also lower than the maximum speed in OVM, while the fluctuation of speed in DSDM is also smaller, which denotes that the perturbation which develops into a congestion pattern in OVM propagates slowly in the DSDM.

We then increased the sensitivity coefficient from 0.5 to 0.8. The traffic congestion in OVM is relieved, but it is still in the stop-and-go congestion pattern (see Figure 3). On the other hand, in the DSDM, the initial perturbation is absorbed and the resulting fluctuation is hardly observable, which means the current traffic flow is stable. The above simulation results show that the DSDM can suppress traffic congestion effectively.

In this subsection, we study the impact of driver heterogeneity (safety headway variation) on traffic flow. We set the sensitivity coefficient $\alpha = 0.4$ and present the speed profiles for all the vehicles in the system at $t = 300$ s.

First, the safety time headway was set to $T_s = 0.6$, which corresponds to a smaller-than-normal distance. Drivers in this situation are called aggressive drivers, and all the cars keep a short headway (corresponding to low speed) with the front vehicle. The traffic system maintains a higher traffic capacity if there is no perturbation, but $\alpha = 0.4$ is an unstable state. When a perturbation is added to the system, the fluctuation of the cars' speed (and thus headway) develops into a stop-and-go congestion pattern (Figure 4), where some

FIGURE 3: Speed profiles for $\alpha = 0.8$, $T_s = 1$ at $t = 300$ s.FIGURE 4: Speed profiles for DSDM with $\alpha = 0.4$, $T_s = 0.6$ at $t = 300$ s.

vehicles run at high speed, while others cannot move at all. There are about 20 vehicles (20%) completely stopped at $T_s = 0.6$ (Figure 4). In macroscopic analysis of traffic flow, this pattern is also called a kink-antikink density wave.

When the safety time headway increases to 0.9, as shown in Figure 4, the perturbation evolves into stop-and-go traffic (see Figure 5), but not to the degree observed in Figure 4. The vehicles caught in congestion in Figure 5 are fewer than those in Figure 4, and congestion tends to dissipate with the increase of safety distance.

We then further increase the safety time headway to $T_s = 1.2$. The profile of car speed over time is shown in Figure 6. The perturbation grows into an unstable traffic flow, but the fluctuation is not as large as that of Figure 5. In Figure 6, the maximum and minimum speed are 1.61 and 0.42, respectively; there is a maximum speed offset 23.08% from the stable velocity of 1.31, while the minimum speed shift

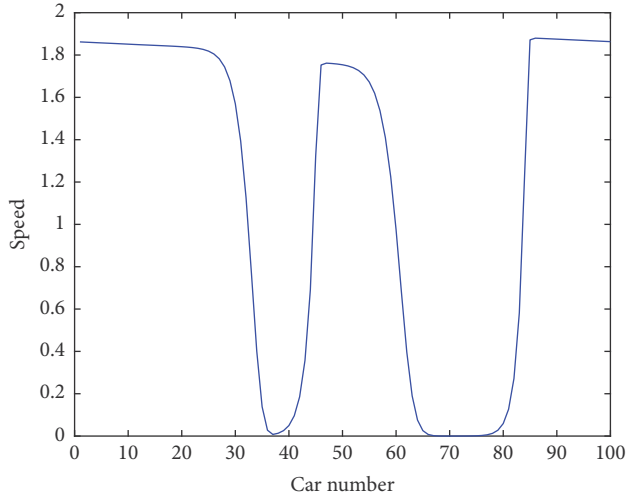


FIGURE 5: Speed profiles for DSDM with $\alpha = 0.4$, $T_s = 0.9$ at $t = 300$ s.

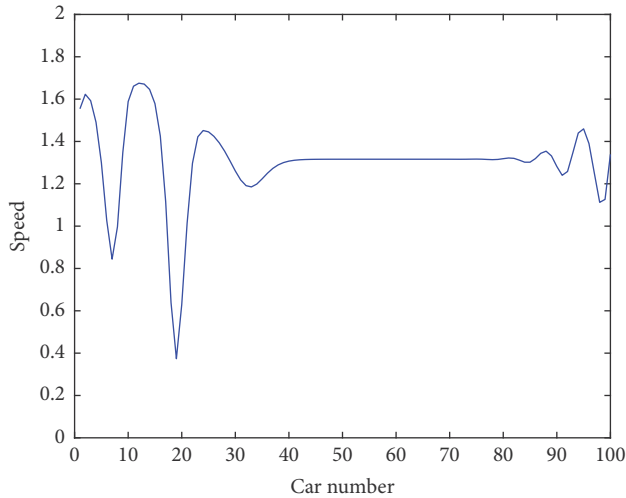


FIGURE 6: Speed profiles for DSDM with $\alpha = 0.4$, $T_s = 1.2$ at $t = 300$ s.

about 67.94%. In this case, stop-and-go traffic disappears and oscillatory congestion occurs.

To understand the impact of safety distance on traffic congestion, we set $T_s = 1.5$. In this case (Figure 7), the traffic congestion was completely eliminated from the traffic system, with a fluctuation of less than 1%. Obviously, this condition is a free flow state.

4. Conclusions

Although the OV car-following model has been extensively investigated by researchers from various fields, all of them used a constant safety distance, which is not consistent with real traffic. In this paper, we propose an extended OVM with dynamic safety distance to study driving behavior. Numerical simulations are conducted to determine the impact of a variable safety distance on the dynamics of traffic stream.

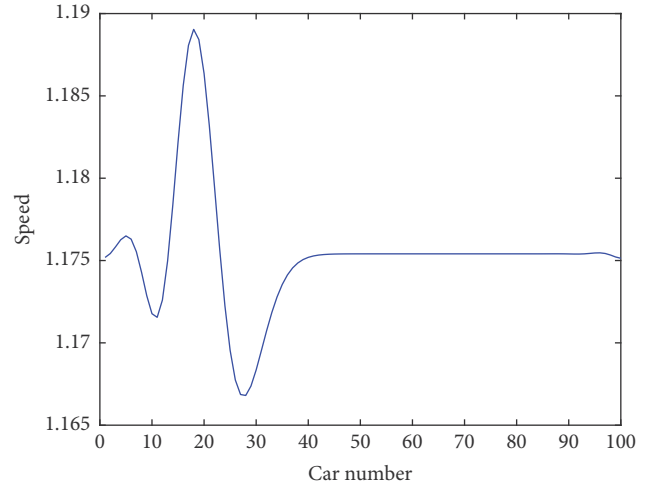


FIGURE 7: Speed profiles for DSDM with $\alpha = 0.4$, $T_s = 1.5$ at $t = 300$ s.

From the simulation results, we obtained the following conclusions:

- (1) A three-dimensional phase diagram is presented to illustrate the impact of dynamic safety distance on the evolution of traffic flow
- (2) Fast-responding drivers (i.e., those with a large sensitivity coefficient) are conducive to the stability of traffic flow
- (3) Conservative drivers (i.e., those with a large safety time headway) can keep road traffic smoother than aggressive drivers
- (4) The proposed model is able to reproduce the observed stop-and-go phase transition

However, the proposed model was only investigated using theoretical analysis and numerical simulations, and the parameters in the model were not calibrated according to real traffic data. In future works, we will use experimental data to explore the effects of variable safety distance on driving behavior.

Data Availability

No data were used to support this study.

Conflicts of Interest

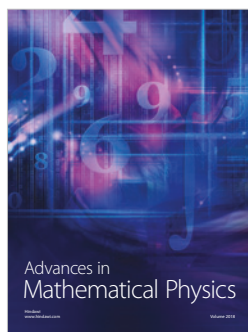
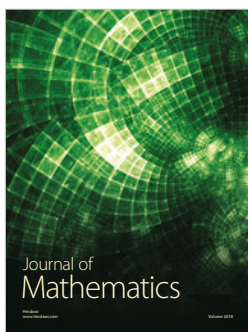
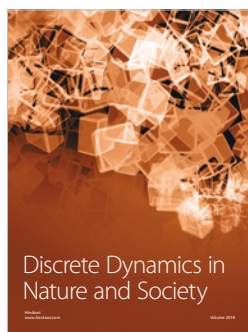
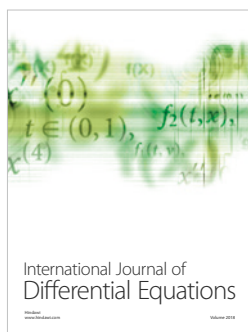
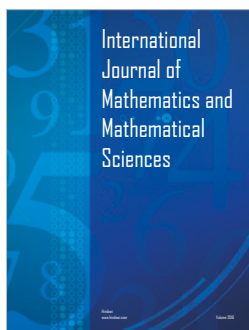
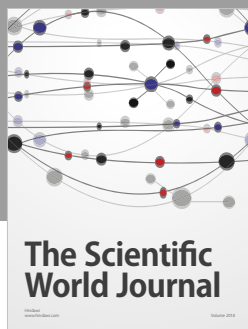
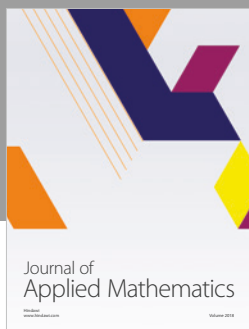
The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This research is supported by the National Natural Science Foundation of China (Grant Nos. 71571109, 71871130, and 71471104).

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