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A new car-following model considering driver's sensory memory

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HIGHLIGHTS

- A new memory car-following model is proposed.
- The memory effects on the stability of traffic flow have been investigated.
- The new car-following model compensates for the disadvantage of the sensory buffer time neglected in existing models.
- The new memory car-following model can convey following car's driver sensing behavior better and avoid the negative velocity in existing models.

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ABSTRACT

This paper presents one kind of new car-following model (mean memory model, simplified as MMM) by introducing driver sensory memory (sensory buffer) term into the original optimal velocity (OV) function by Bando et al. (1995, 1998). The main improvement is that MMM can avoid the disadvantage of the sensory buffer time neglected in existing models. The stability condition of the proposed model is obtained by using linear stability theory. Results show that the stability region decreases when the driver's sensory buffer time increases. Furthermore, the model is investigated in detail by numerical methods. The following conclusions are derived. (a) Numerical results of starting process for the car motion under a traffic signal accord with empirical traffic values; (b) the numerical simulations in the form of the space–time evolution of headway and velocity are also in good agreement with the theoretical analysis; (c) the size of hysteresis loops will be reduced with the sensing buffer time decreasing. Both analytical and simulation results show that the following car driver's sensory buffer time plays an important role on the stability of traffic flow.

1. Introduction

Currently, road traffic congestion and jam are becoming more and more serious. Various car-following models are developed to investigate its evolution mechanism in the past decades. Among them, several epochmaking models are particularly important, many subsequent car-following models were proposed on the inspiration of them. (a) The seminal works (original linear models) by Pipes [1] and Chandler et al. [2], (b) the early nonlinear models presented by Herman et al. [3], Gazis et al. [4,5] and Newell [6], (c) the recent optimal velocity model (OVM) of Bando et al. [7]. Subsequently, many extended

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traffic models [8–40] have been presented with the consideration of different traffic factors on the basis of them, especially based on OVM.

However, all of the above models exclusively depend on traffic states at present time t, namely, the past traffic states of the leading car have not been considered in them. In real traffic, the past information of traffic flow has an important effect on a driver during his/her running process. Zhang [41] pointed out that a driver has memory if his speed at a later time depends on his speed at a previous time and developed a macro model by incorporating the effect of driver's memory. Subsequently, Tang et al. [42] presented a car-following model with driver's memory and Peng et al. [43] presented a driver's memory lattice model of traffic flow. By observing the actual traffic behavior of the driver, Herman et al. [3] found that the driver during his/her running process will leave the memory of past information. That is to say, driver's memory should be taken into account in the traffic model. Based on the original OV model [7], a kind of new OV model is proposed in this paper by incorporating driver's memory time term. However, models in Refs. [42,43] are based only on a point memory only at the previous time $t - \tau_0$, they neglected the states between $t - \tau_0$ and t. In real traffic world, in order to get relatively reliable and stable predecessor driving states and trends, the following car driver always need a period of time (such as from $t - \tau_0$ to t) to accomplish perceiving, understanding and projecting predecessor driving states and trends process. Hence, this time has been thought to be unavoidable and is essential to construct realistic traffic flow models and understand traffic kinematics and dynamics. Simultaneously for reasons of simplification, we only consider distance headway and take the mean value of headways in a period of time $[t - \tau_0, t]$ as the driver's sensing headway and desired velocity motive force. Thus, a desired velocity model based on a continuous sensing of leading car's motion states in a period of time $[t - \tau_0, t]$ is formed, not only on present time point t and the previous time point $t - \tau_0$, but also on their gaps. This is the main difference of our model from previous models including memory models [42,43]. Further, an improved car-following model with considering driver's memory effect is proposed as follows in Section 2. We call it mean memory model (for short, MMM).

2. Models

2.1. Continuous model definition

Considering continuous traffic states in $[t - \tau_0, t]$, an integral desired velocity function is constructed as the following Eq. (1),

$$\frac{\mathrm{d}x_n(t+\tau)}{\mathrm{d}t} = V\left(\frac{1}{\tau_0}\int_{t-\tau_0}^{t} \Delta x_n(u)\mathrm{d}u\right), \quad u \in [t-\tau_0, t] \tag{1}$$

where $\Delta x_n(u) = x_{n-1}(u) - x_n(u)$ is the headway between the preceding car $n-1$ and the following car n, respectively; $x_{n-1}(u)$ and $x_n(u)$ represent the positions of the car $n-1$ and the car n at time u; τ is the following car velocity response time; τ_0 is the driver sensory memory time; V is the desired velocity function. In order to derive the acceleration, we give the one-order Taylor series expansion about τ on the left-hand term of Eq. (1) and obtain Eq. (1) as

$$\frac{\mathrm{d}x_n(t+\tau)}{\mathrm{d}t} = \frac{\mathrm{d}x_n(t)}{\mathrm{d}t} + \tau\frac{\mathrm{d}^2x_n(t)}{\mathrm{d}t^2} + o(\tau) = v_n(t) + \tau\frac{\mathrm{d}v_n(t)}{\mathrm{d}t} + o(\tau) \tag{2}$$

where $o(\tau)$ are the higher-order terms of τ. By ignoring the higher-order terms, we have

$$\frac{\mathrm{d}v_n(t)}{\mathrm{d}t} = \alpha\left(V\left(\frac{1}{\tau_0}\int_{t-\tau_0}^{t} \Delta x_n(u)\mathrm{d}u\right) - v_n(t)\right) \tag{3}$$

$\alpha = 1/\tau$ is the driver's sensitivity coefficient; Eq. (3) shows that the following car's acceleration at time t are determined by the mean optimal velocity in $[t - \tau_0, t]$ and the present velocity at t.

2.2. Definition of a discretization scheme

The discretization scheme can be written as:

$$\frac{\mathrm{d}x_n(t+\tau)}{\mathrm{d}t} = V\left(\frac{1}{m}\sum_{i=1}^{m} \Delta x_n(u_i)\right), \quad u_i \in [t-\tau_0, t]. \tag{4}$$

By ignoring the higher-order terms of Taylor series expansion about τ on the left-hand term of Eq. (4) and obtain Eq. (4) as

$$\frac{\mathrm{d}v_n(t)}{\mathrm{d}t} = \alpha\left[V\left(\frac{1}{m}\sum_{i=1}^{m} \Delta x_n(u_i)\right) - v_n(t)\right], \quad u_i \in [t-\tau_0, t]. \tag{5}$$

By Mean Value Theorem of Integrals, there must be a $\tau_1 \in [t - \tau_0, t]$, let

$$\Delta x_n(t-\tau_1) = \frac{1}{\tau_0}\int_{t-\tau_0}^{t} \Delta x_n(t)\mathrm{d}t. \tag{6}$$

(In the discretization case, the right-hand term of Eq. (6) is $\frac{1}{m}\sum_{i=1}^{m} \Delta x_n(u_i)$, $u_i \in [t - \tau_0, t]$.)