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Application of a Boltzmann-entropy-like concept in an agent-based multilane traffic model

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ABSTRACT

We discuss the dynamics of an agent-based multilane traffic model using three defined rules. The dynamical characteristics of the model are described by a Boltzmann traffic entropy quantity adopting the concept of Boltzmann entropy in statistical physics. The results are analyzed using fundamental diagrams based on lane density, entropy and its derivative with respect to density. We show that there are three classifications of allowed initial to equilibrium state transition process out of four possibilities and demonstrate that density and entropy fluctuations occur during the transition from the initial to equilibrium states, exhibiting the well-known expected self-organization process. The related concept of entropy can therefore be considered as a new alternative quantity to describe the complexity of traffic dynamics.

1. Introduction

A major cause for traffic problems worldwide is the increasing number of vehicles. This has led to decades of investigations in order to understand the complex dynamical characteristics of traffic flow. There are currently three categories of traffic models. These are the macroscopic models, microscopic models, and mesoscopic models.

The first attempt to model traffic flow macroscopically was conducted by Greenshields who introduced his first fundamental diagram in 1934 describing the relation between lane density and speed [1]. Afterwards, Lighthill, Whitham and Richards [2,3] have conducted analytical works now known as the LWR model, whereas other analytical-based traffic models have also been reported in Refs. [4–7]. The main physical formula in macroscopic-based models is expressed using a mass conservation law, whereas the vehicles are assumed to occupy the lane continuously. The vehicle dynamics can then be generally described using hyperbolic nonlinear partial differential equations as a function of its density and speed. Remarkably, an emerging phenomenon was reported in the corresponding macroscopic traffic flow, e.g. the emergence of a shock wave in the LWR model [3].

In the microscopic models, space is described in discrete form, and the vehicles are assumed to follow certain interaction rules. The first microscopic model is the car-following model [8–10], where time is considered to be continuous such that the dynamics of each vehicle is described by a differential equation of its position and speed. The model usually accommodates only a single lane due to the difficulty in handling vehicle maneuvers to other lanes. Recently, this model was further intensively improved by Tang et al. in Refs. [11–15]. The second type is the agent-based model also known as the cellular automata model. Some examples of this model are the Nagel–Schreckenberg [16], Biham–Middleton–Levine [17,18] and other models mentioned in Refs. [19,20]. Unlike the car-following model, here both space and time are considered discrete. In addition, adding another lane is now much easier to handle. Generally, the definition of a single vehicle behavior and its interaction with other vehicles is the most crucial development step in the agent-based model. Based on this, the model can be classified into either deterministic or stochastic. Mesoscopic model [21,22] combines the two previous models. Here, the aggregate behavior of all vehicles is represented by a specific probability distribution function while still considering the individual behavior of each vehicle which is following specific rules.

Nevertheless, it should be noted that all explained models failed to describe the congested problem that arise in the real traffic [23]. Recently, Kerner et al. [24–29] have proposed a three-phase traffic flow theory based on fundamental empirical features of real traffic

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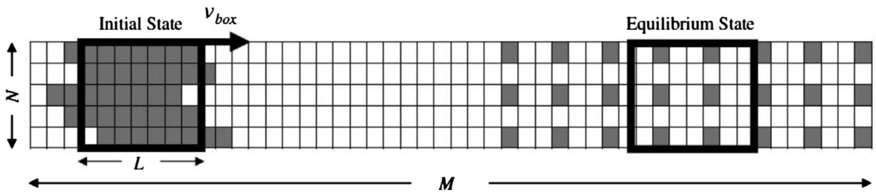

Fig. 1. Illustration of traffic-entropy-transition process. The box with thick border moves with speed v_{box}.

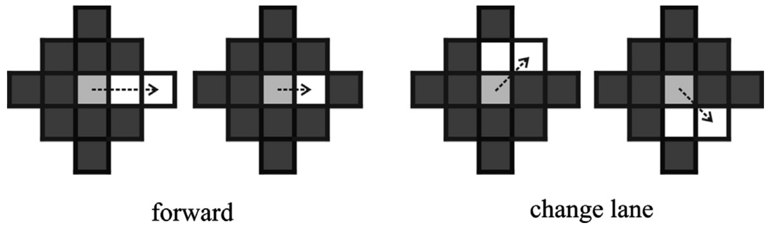

Fig. 2. Illustration of the defined rules in Neumann neighborhood.

in order to give a physical explanation on the traffic breakdown due to transition from free to congested traffic flow by introducing the concept of free flow, synchronized flow and wide moving jam phases. In principle, this empirical concept can be applied both in the macroscopic [24,25] and microscopic models [26–29]. In the mean time, the effects of the other important factors such as road condition, traffic information as well as driver's attribution to the dynamics of real traffic have also been discussed in Refs. [11–15, 30–33].

A relatively comprehensive historical review of all these three different traffic models can be seen in Ref. [34]. However, it is interesting to point out that the multilane traffic flow is one of the important topics for model based investigation, e.g. Ref. [7]. In our understanding, little effort has been performed to describe the corresponding internal dynamics. Based on this fact, instead of using the existing traffic model, we have developed in this work a simple agent-based multilane traffic model with three defined rules and consider a Boltzmann traffic entropy quantity to study its internal dynamics, namely the characteristics of vehicles spatial distribution and its behavior as a function of lane density. To the best of our knowledge, the discussion regarding the application of the corresponding Boltzmann-entropy-like concept in a microscopic traffic model has never been reported elsewhere.

Here we emphasized for the sake of clarity that the defined Boltzmann traffic entropy applied in this work has a different physical interpretation compared to the Boltzmann entropy concept in statistical physics. Nevertheless, we will show that it can be useful to describe the internal dynamics of spatial vehicles distribution of an agent based multilane traffic model.

We organize our results in this work as follows: the model is explained in Section 2, followed by the definition of the traffic entropy. The associated fundamental diagrams and types of possible internal dynamical process are given in Section 3. In Section 4, we present the results of our simulation and discuss the corresponding dynamics. Finally, we present our summary in Section 5.

2. Agent-based traffic model and Boltzmann traffic entropy

The computational window is defined in the form of $M \times N$ grid cells which can either be occupied or unoccupied by a vehicle. The total number of vehicles is given by n and the number of available cells that can be filled along the horizontal direction is denoted by M, while N represents the number of lanes. The initial system is defined by a box with $L \times N$ cells as shown in Fig. 1, where L denotes the number of cells along the horizontal direction and is occupied by n_{box} number of vehicles, while the rest is denoted by $n_o = n - n_{box}$ and are outside the system. The position of each vehicle is denoted by $r(i, j)$. The dummy indices i and j indicate the corresponding position where $r(0, 0)$ is located at the top-left corner of the computational window.

We consider the second order Neumann neighborhood as depicted in Fig. 2, and define the following three rules:

Rule 1: Check the two cells located in front of the vehicle (occupied cell). If the cells are unoccupied then the vehicle moves two cells forward otherwise go to Rule 2.

Rule 2: Check one cell in front of the occupied cell. If it is unoccupied, then the vehicle moves one cell forward, otherwise proceed to the Rule 3.

Rule 3: Check the two cells that are positioned as follows: one cell is directly located to the right or left of the occupied cell, and one directly in front of the former (in this case the right or left forward diagonal cell of the occupied cell) as shown in Fig. 2b. If the related cells of either the right or left lane are unoccupied, then the vehicle moves diagonally to the unoccupied lane. If both cells on the right and left lanes are unoccupied at the same time, then the vehicle decides randomly whether to move diagonally to the right or left lane. If neither option is possible the vehicle does not move. A vehicle at the leftmost lane can only change to the right lane and vice versa.

In our algorithm, we perform an iteration process and denote its number as time-step t. For every iteration step the above rules are applied consecutively to every vehicle in the related state such that it changes its position accordingly and so on. It is important to note that the developed algorithm is designed so that the rules apply simultaneously for all vehicles, and that Rule 1 obviously results in an equilibrium state where the distance between two adjacent vehicles in the horizontal direction is two cells. Here, we define the equilibrium state as a state where the above mentioned rules can no longer change it.

It has to be emphasized from the beginning that although the velocity of each vehicle at equilibrium is uniform but different initial states can lead to different equilibrium states. Starting from the initial state, the state changing process will continue until a new equilibrium state is reached. In this work, we consider M being large enough such that no boundary condition in the flow direction is needed in our calculation. We are fully aware though, that compared to the real traffic, our model is subject to certain limitations. For instance, our model does not take into account the hetero-