SIMULATION RESEARCH ON TRAFFIC FLOW OF AUTOPILOT BASED ON CELLULAR AUTOMATA

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Combining the autopilot model from Arnab Bose with the classic NaSch model, a single-lane cellular automaton traffic flow model suitable for self-driving is proposed. A simulation analysis was conducted to investigate the driving condition of the self-driving vehicle in the Matlab environment, it is found that the simulation results present the characteristics of traffic flow in the autopilot environment. In addition, it was found that the setting of different headway in automatic driving has a great influence on road capacity and congestion, the capacity of 0.5s headway is about 4 times that of 3s headway, When the headway is reduced from 4s to 1s, the traffic jam can be reduced by about 95%, which can be used as a strategy to alleviate the jam.

Keywords: combining the autopilot model; the traffic jam; spacing; cellular automata

1. Introduction

In recent years, with the continuous development of advanced high-tech and autonomous vehicle technologies such as the computer, information, manufacturing, and the use of intelligent technology in vehicles and infrastructure, the transportation system has become more efficient. Auto-driving vehicles have become one of the most cutting-edge technologies of today’s attention, and the future road traffic system is likely to be completely renewed. In the near future, autonomous vehicles will become mainstream. Research on the traffic flow of autonomous vehicles is of great significance to alleviate traffic congestion, improve road utilization and road safety.

The cellular automatic model is a widely used mathematical model [2-5]. Due to the characteristics of the cellular automaton, it has developed rapidly in the transportation field and became one of the hot research issues in the transportation field in the late 20th and early 21st century [6-9]. The 184 rule proposed by Wolfram in 1986 was an original cellular automaton traffic flow model, Nagel and Schrenberg put forward the classic NaSch model (NS model) based on the 184 rule [6]. Compared with the No. 184 model, the main improvement of this

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model takes random slowing probability into consideration and adjusts the maximum velocity. Although the model rules are simple, they can simulate complex traffic conditions such as start-stop wave phenomenon, free-flow state, and congestion flow state. Based on the NS model, many improved models were suggested such as TT model [8], FI model [10], sensitive driving model [11], safe driving model [12], etc. which greatly enriched and improved the research of highway traffic flow. However, these studies underestimated the impact of vehicle characteristics on the driving performance of self-driving vehicles.

Traffic congestion will seriously affect the traffic efficiency, and it may cause traffic accidents such as rear-end collisions. Many previous studies made effort to understand the propagation of traffic jams [13]. To reduce the traffic congestion, scholars have investigated the effect of many factors on the traffic congestion, such as driving velocity, driving behavior, road type, etc [14-16]. The self-driving vehicles was considered as an effective way to reduce traffic congestion [17]. Maciejewski and Bischof [18] pointed out the higher market penetration rate help to reduce the traffic congestion. In order to improve the ability of reducing congestion of self-driving vehicles, it is necessary to study the influence of vehicle characteristics on the driving performance of self-driving vehicles.

Therefore, to investigate the effect of vehicle characteristics on driving performance of self-driving vehicles and congestion. This paper comprehensively considered the autonomous driving environment and the physical characteristics of the self-driving vehicle. By combining the automatic driving model of Arnab Bose [1] with the classic NS model, a single-lane cellular automaton traffic flow suitable for autonomous driving was proposed. In addition, the cell size was refined to build the model more accurate and present the traffic flow characteristics in the autonomous driving environment. The simulation was carried out in the Matlab environment, and the traffic flow characteristics in the automatic driving environment were analyzed. The effects of headway distance on traffic flow and congestion were summarized.

2. Model construction

In order to make the newly established model closer to the actual traffic, the physical dimensions of the vehicle, the acceleration and deceleration performance, and the reaction time of the driver are comprehensively considered. The vehicle performs a control strategy of velocity and position with consideration of the difference between the target spacing G and expected spacing D. Among them, the target spacing $G = h_a v$, h_a is the headway distance, considering the velocity of the preceding vehicle, $D - G = K$, the schematic diagram is shown in Fig. 1.

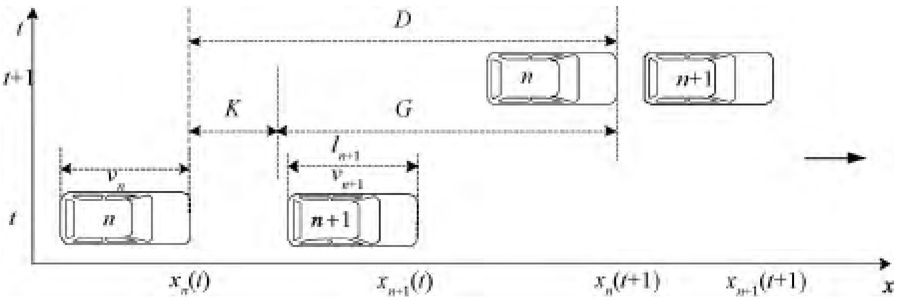


Fig. 1. Automatic driving diagram

1) While the running of the vehicle, the expected distance of the current car in the next second is greater than the target distance required, that is, when $D > G$, the corresponding update rules can be executed according to the following conditions:

(a) When $K > v_n\Delta t$, $0 < D - G \le v_n\Delta t + 0.5a_{\max}(\Delta t)^2$, the vehicle accelerates according to the following rules:

$$v_n\Delta t = \min(\min(D - G, v_{\max}\Delta t), Gap) \tag{1}$$

When $K > v_n\Delta t$, $D - G > v_n\Delta t + 0.5a_{\max}(\Delta t)^2$, the vehicle accelerates according to the following rules:

$$v_n\Delta t = \min\left(\min\left(v_n\Delta t + 0.5a_{\max}(\Delta t)^2, v_{\max}\Delta t\right), Gap\right) \tag{2}$$

(b) When $K < v_n\Delta t$, $v_n\Delta t - 0.5b_{\max}(\Delta t)^2 < D - G \le v_n\Delta t$, the vehicle decelerates according to the following rules:

$$v_n\Delta t = \min(D - G, Gap) \tag{3}$$

When $K < v_n\Delta t$, $D - G < v_n\Delta t - 0.5b_{\max}(\Delta t)^2$ is reached, in order to meet the target distance, the vehicle decelerates with the maximum deceleration, and the shortest distance traveled, that is, approaches the target distance. The vehicle decelerates according to the following rules:

$$v_n\Delta t = \min\left(\max\left(v_n\Delta t - 0.5b_{\max}(\Delta t)^2, 0\right), Gap\right) \tag{4}$$

(c) When $K = v_n\Delta t$, the vehicle is driven at a constant velocity while ensuring that the vehicle is safe to drive:

$$v_n\Delta t = \min(v_n\Delta t, Gap) \tag{5}$$

2) While the running of the vehicle, the expected distance of the current vehicle less than the target distance required by the vehicle n, that is, when $D \le G$, the vehicle adopts the deceleration driving.

$$v_n\Delta t = \min\left(\max\left(v_n\Delta t - 0.5b_{\max}(\Delta t)^2, 0\right), Gap\right) \tag{6}$$

3) Location update

On the basis of the velocity update rules, the vehicle position update is performed as shown in equation (7).

$$x_{n+1} = x_n + v_n \Delta t \tag{7}$$

Where: Gap is the distance between the front and rear cars, that is, $Gap = x_{n+1} - x_n - l_{n+1}$; $x_n(t)$ is the position of the n^{th} vehicle at time t; $x_{n+1}(t)$ is the position of the preceding vehicle of the n^{th} vehicle at time t; l_{n+1} is the length of the preceding vehicle; $a_{\max}$ is the maximum acceleration while the running of the n^{th} vehicle; $v_{\max}$ is the maximum driving velocity while the running of the n^{th} vehicle; $b_{\max}$ is the maximum deceleration of the n^{th} vehicle; Δt is the simulation time step.

3. Autopilot traffic flow analysis

3.1. Simulation settings

In order to show the acceleration and deceleration characteristics of the car in the autopilot environment more realistically and flexibly, this paper simulates a single lane with a discrete cell chain of length L, and the length is set to 5km. In the simulation, each cell is 0.5m, and the schematic diagram of the vehicle occupying the road cell is shown in Fig. 2. Using periodic boundary conditions, in the initial state, N vehicles are evenly distributed on the road. The simulation time step and the size of the cell can be adjusted with consideration of the maximum velocity limit. The initial velocity of the vehicle is randomly selected at $(0, v_{\max})$. The total traffic density on the driveway is ρ, $\rho = \frac{N}{L}$. The average velocity of vehicles at time t is $\bar{v}(t), \bar{v}(t) = \frac{1}{N}\sum_{n=1}^{N} v_n(t)$. The evolution time is 104 steps, and the vehicle velocity in the last 1000 time steps of the evolution are recorded, and the average is performed twice, and the average velocity $\bar{v}(t)$ of each operation is obtained.

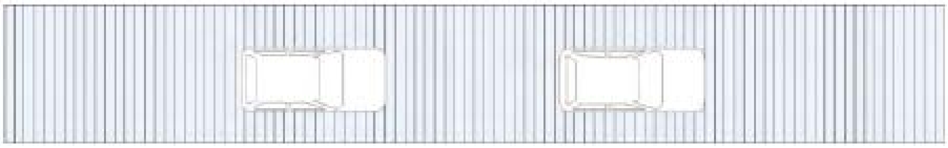
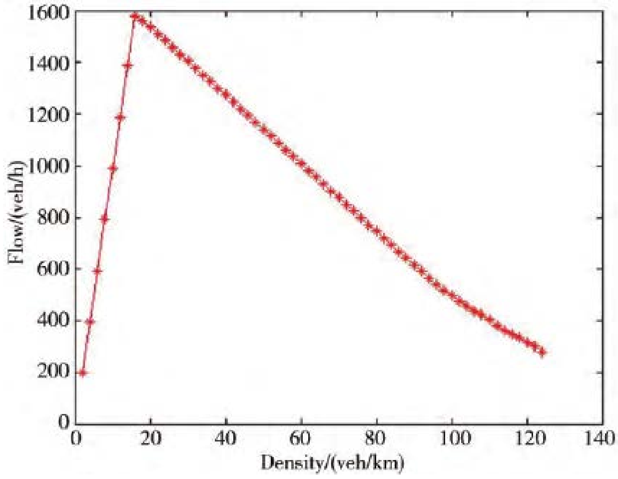


Fig. 2. Vehicle occupying cell diagram

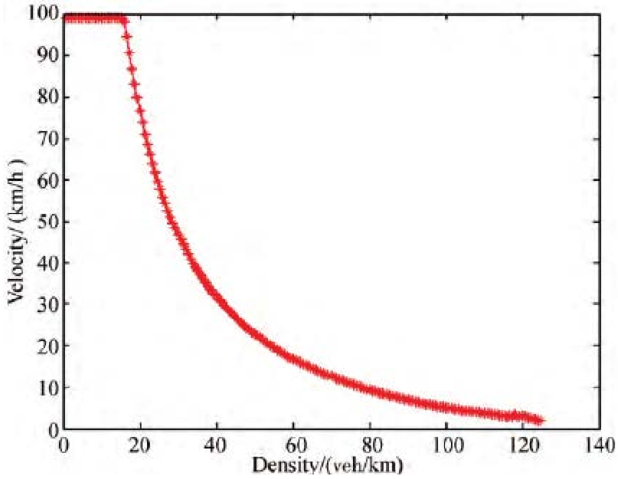
3.2. Flow-close- velocity *basic diagram analysis*

Combined with the physical characteristics of the self-driving vehicle, the simulation analysis is carried out on the basis of the built model, and the

MATLAB program is carried out considering the safety, the characteristics of the automatic driving. A basic characteristic of the traffic flow model is to correctly present the relationship between flow and density. The flow, density, and velocity data are obtained by simulation using a cellular automaton, as shown in Fig. 3, where the parameter $v_{\max} = 75$ km/h, each small the car is 7.5m long and occupies 15 cells, which is equivalent to 1s per time step. It can be seen from Fig. 3 that it is a free flow when the density is lower than the critical density and it is a crowded flow when the density is higher than the critical density. The flow, density, and velocity basic diagrams well demonstrate the characteristics of traffic flow in the autonomous driving environment.



(a)



(b)

Fig. 3. Basic diagram

In addition, through the analysis and development of the established autopilot model and the corresponding velocity position update rules, it can be seen that the headway distance is a key parameter, which is also the microscopic parameter of the traffic flow. The general headway time is 2-3s. In this paper, the automatic driving is realized by reducing the headway, and Fig. 4 is obtained from simulation. It can be seen that when the headway is 0.5s, the traffic capacity is about four times of that when the headway is 3s. Therefore, the road capacity is greatly improved by reducing the time headway.

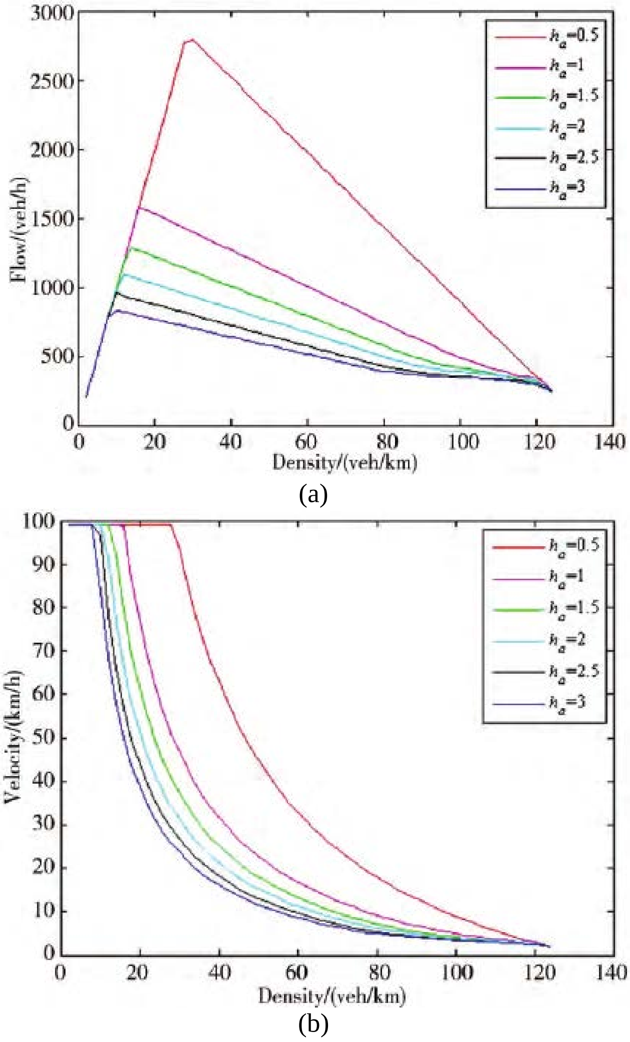


Fig. 4. Basic diagram of different time headway intervals

3.3 Analysis of the influence of time and space characteristics of traffic flow under different time headway

In this paper, the congested vehicle is defined as a vehicle with a velocity of less than 10 km/h. The corresponding traffic congestion level is described by the vehicle's congestion ratio CR. The calculation formula of the congestion ratio CR is as follows:

$$CR = \frac{n'}{\Delta TN} \tag{8}$$

Where: n' is the number of congested cars; ΔT is the last 1000 time step simulation time in the simulation. In the simulation setup, the evolution time is 10^4 steps, and all the vehicle velocity in the last 1000 time steps of the evolution are recorded, where ΔT is the last 1000 steps in the 10,000 steps of the simulation evolution time step; N is the total number of cars.

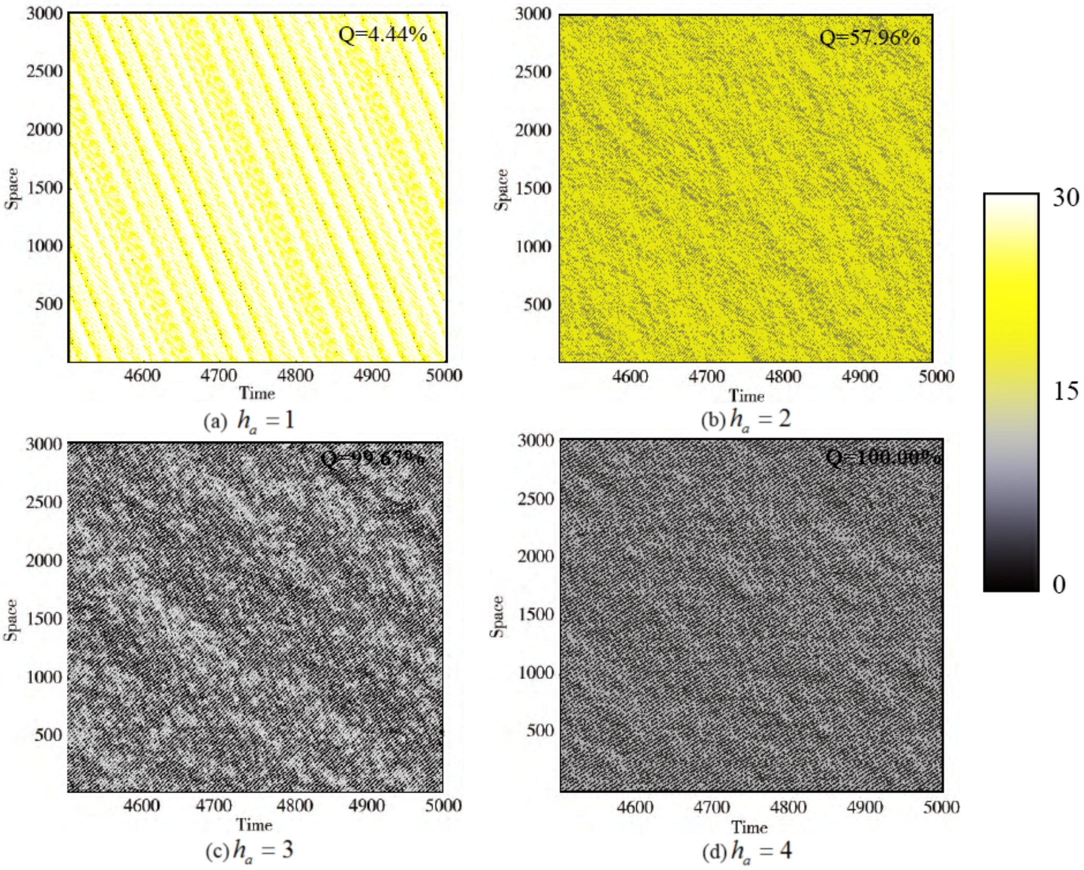


Fig. 5. Velocity-time-space diagram

Fig. 5 are diagrams show the velocity-time-space distribution of different headway distances h_a. Headway distance was obtained by simulating traffic based on the cellular automaton automatic driving model. These four figures show that the vehicle driving velocity in different driving conditions. It can be seen that when the system density is given as 60 veh/km, the congestion ratio increases with h_a. When the headway is $h_a = 1s$, the congestion ratio is very small, 4.44%, and when the headway is $h_a = 4s$, the heavy congestion was happened. It can be seen that reducing the time headway in the automatic driving model can greatly reduce traffic congestion.

Fig. 6 shows the trend of the congestion proportion as headway distance increases at different levels of density. It can be seen that the congestion ratio increased with the headway distance; when $\rho = 20$ veh/km is given, it is basically not congested; when given $\rho = 40$ veh/km, the headway is less than 2.5s, it is not congested. When it is higher than 2.5s, the headway distance is increased, and the congestion ratio increased rapidly. When the $\rho = 60$ veh/km is given, the congestion ratio is almost unaffected after the headway is less than 1s and higher than 2.5s. This again confirms that reducing h_a can effectively control traffic congestion with the automatic driving model. It can be concluded that effectively adjusting h_a can eliminate or alleviate traffic congestion to some extent.

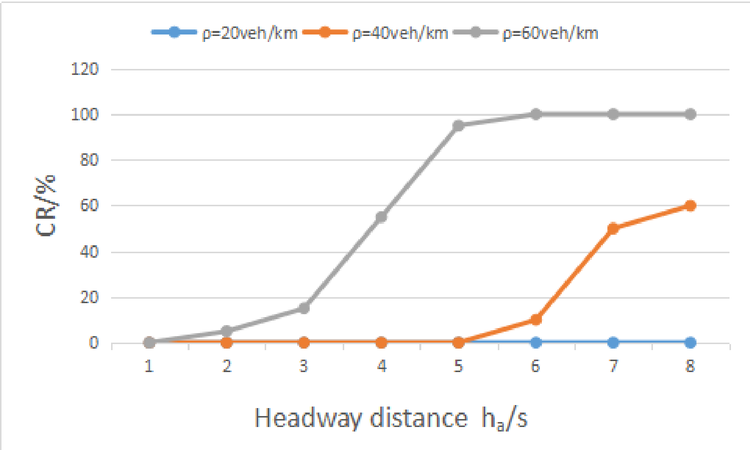


Fig. 6. Congestion ratio diagram at different levels headway time intervals

4. Conclusions

This paper investigated the effects of autonomous driving technology, vehicle characteristics (including length, acceleration and deceleration, reaction time, velocity, etc.) on driving behavior, refined the length of the cell, and combined the Arnab Bose automatic driving model with the classic NaSch model. A single-lane cellular automaton traffic flow model for autonomous driving was proposed. Through numerical simulations, the size of the cell is 7.5m in most cellular automaton models and classic NS models. The size of the cell in the model established in this paper is 0.5m and the length of the vehicle is 7.5m. In the simulation, the vehicle moved forward by at least one cell per second, is 7.5

m. This obviously does not in line with the actual situation, but in the new model built, the cell is refined to 0.5m, and the vehicle movements can be more realistic. This model is a good example to show the traffic flow characteristics in an autonomous driving environment. The study suggested that the traffic capacity at a headway of 0.5s is about four times the capacity of the headway at 3s. When the headway distance is reduced from 4s to 1s, traffic congestion can be reduced by about 95%. In addition, by comparing the corresponding congestion ratio value CR at the same density, it can be seen that the headway time is continuously increased, and the congestion of the traffic flow is gradually intensified. Reducing the headway distance can greatly improve road capacity while mitigating traffic congestion. This finding will help to design the further autonomous vehicle that can reduce the congestion.

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R E F E R E N C E S

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