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A Hybrid Model of Smart Cars Based on Cellular Automata

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Abstract

This paper is based on the cellular automata model, considering the situation of mixing into smart cars, and improving the model accordingly, considering the vehicle lane change and interaction in the case of two lanes. For the mixed traffic flow of manual and autonomous vehicles, the two Carry out combined analysis on this vehicle.

Keywords

Cellular automata model, Smart cars, Mixed traffic flow.

1. Introduction

With the continuous progress of society, rapid economic development, science and technology are also advancing by leaps and bounds. The automotive industry is one of the typical fields. In recent years, a series of advanced sensors, controllers and solutions have created the birth of smart cars to solve traffic problems. Problems such as congestion, road safety, energy consumption and environmental pollution. Self-driving cars, also known as driverless cars, computer-driven cars, or wheeled mobile robots, are smart cars that realize driverless driving through a computer system. It has a history of decades in the 20th century, and the beginning of the 21st century showed a trend close to practicality. Because the cost and price of self-driving cars are high, it will inevitably go through a relatively long process to fully popularize automatic driving from manual-driving cars. The content of this paper is about the driving state of the mixed traffic flow of manual driving cars and smart cars that may exist in this process.Organization of the Text.

The development of intelligent transportation systems consists of three stages: the first stage is dynamic perception, that is, real-time acquisition of traffic information covering the entire network of roads, and the establishment of a big data platform for dynamic perception; the second stage is active management, that is, providing active planning, Active traffic control, active command and dispatch, active public services and other dynamic management services; the third stage is intelligent network connection, that is, the realization of vehicle networking, vehicle-road collaboration, automatic driving, etc. [1]. The intelligent networked car is an organic combination of the Internet of Vehicles and smart cars. It is equipped with advanced on-board sensors, controllers, actuators and other devices, and integrates modern communication and network technologies to realize the intelligence of cars and people, cars, roads, and backgrounds. Information exchange and sharing, to achieve safe, comfortable, energy-saving, and efficient driving, and finally a new generation of cars that can replace humans. The essence of the Internet of Vehicles is to realize the integration and interaction of people, vehicles, networks, roads, and things [2]. Many scholars have studied the driving characteristics of intelligent vehicles. You Feng [3] studied the conditions to prevent vehicle collisions when changing lanes, and gave a calculation method for the minimum safe distance between lanes. A polynomial-based trajectory algorithm is selected as the method of trajectory planning for automatic lane changing and overtaking. The paper by Guo Jinghua et al. [4] introduced the research and application development status of intelligent vehicle motion control technology at

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home and abroad in the past ten years, and looked forward to the future research ideas of intelligent vehicle motion control, laying a foundation for improving the comprehensive performance of intelligent vehicles in the future. basis.

It has become one of the typical methods to use cellular automata to simulate the microscopic motion state of vehicles in traffic flow to understand the interaction mechanism between vehicles. Dong Changyin et al. [5] established a driving cellular automaton model based on comfort, simulated and analyzed the off-ramp mixed with smart cars, introduced parameters such as vehicle perception range, lane-changing control area, lane-changing risk factors, and established a control vehicle Free lane changing and forced lane changing models for lateral movement. Zhang Peng [6] introduced the classification of lane change and the influencing factors of lane change, and described the process of free lane change and forced lane change intention generation. From the perspective of microscopic factors, the influence of headway and speed difference on lane changing time is analyzed. Then it analyzes the mutual influence and game effect between multiple vehicles when the vehicle is driving on the road, analogy to the principle of potential energy field, and puts forward the concept of multi-vehicle interaction area, the decision of lane change, the interaction between lane change vehicles and surrounding vehicles the speed change is attributed to a function of the overlapping area of the multi-vehicle interaction area. Combining the update rules of cellular automata, a multi-vehicle interactive lane changing model is established, which correlates the interactive behavior of vehicles with the overlapping area of the interactive area, and quantitatively describes the speed changes of interactive vehicles. Hua Xuedong et al. [7] used a two-lane cellular automaton model to analyze the characteristics of urban road traffic flow considering driving psychology. In view of the different psychology of the driver in lane changing and deceleration and braking when driving on urban roads, the choice of lane changing probability Ps and the safety parameter λ which reflect the driving psychology are respectively introduced. Through computer simulation, the different lane changing probabilities and the relationship between vehicle speed, density and flow under the condition of safety parameters, and the influence of different driving psychology on the traffic system is analyzed.

2. Different types of vehicle operation classification

Two cars following the car on the road can be simplified as shown in Figure 1.

Fig. 1 Schematic diagram of the following position of the two cars

In the case of a smart car-manual driving car hybrid, it can be divided into four categories:

1) The car in front is a manually driven car, and the car behind is a smart car.

2) The car in front is a smart car, and the car behind is a manually driven car.

3) The front car and the rear car are all smart cars.

4) The cars ahead and behind are all manually driven cars.

In this article, a smart car is defined as an intelligent networked car, which can communicate with road facilities and other vehicles, and can obtain information such as the speed and location of the vehicle. Compared with smart cars, manual driving cars can only be judged by the driver. There is still a certain deviation between human judgment and specific data, so when building a motion model, it is discussed separately.

As shown in Figure 2, for a vehicle n_i in the inner lane, the preceding car is n_{i-1}, the following car is n_{i+1}, the preceding car in the adjacent lane is n_{j-1}, and the following car is n_j. Vehicle n_i is

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located here, you can choose whether to change lanes at this time. It can be divided into the following situations:

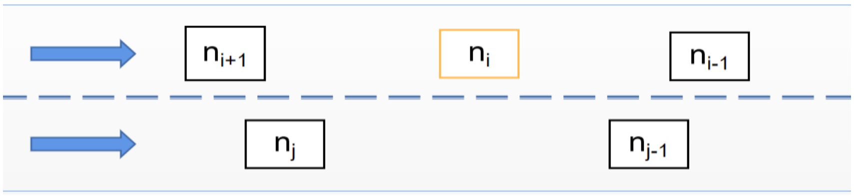

Fig. 2 Schematic diagram of vehicle operation

1) Keep the original lane and choose the maximum speed to move forward while ensuring safety.

2) When $v_i > v_j$, keep the original speed and change lanes to before n_j, and keep a safe distance from the preceding vehicle nj-1.

3) When $v_i < v_j$ and n_j cooperate with deceleration, keep a constant speed and change lanes before nj.

4) When $v_i < v_j$, n_i accelerates to change lanes before n_j.

5) When $v_i < v_j$, n_i slows down and waits for lane change to n_j.

In the process of changing lanes, you need to compare the speed of the following vehicle. In the above process, whether or not to change lanes, you need to consider the safety distance from the vehicle ahead at the next moment. The research in this paper is based on the premise that traffic can travel at maximum speed. So only discuss the first four situations.

In the process of model building, we assume that CAVs can cooperate well with decelerating and changing lanes, and the driver can only control the speed based on experience.

3. Build a cellular automata model

3.1 NS model and STCA model

In the NS model, both space and time are discretized. The vehicles are distributed on a one-dimensional discrete cell chain. Each cell has two states: ① vacant; ② occupied by a car. Let $v_n(t)$, $x_n(t)$ and $d_n(t)$ respectively represent the speed, position and head distance of the n th car at time t, where the speed $v_i \in [0, v_{max}]$, v_{max} is the maximum speed, and the parameters are introduced at the same time p represents the random deceleration probability of the vehicle. The NS model uses the following rules to update the state of each vehicle from $t \to t+1$: ① accelerate, $v_n = \min\{v_{n+1}, v_{max}\}$; ② decelerate, $v_n = (v_n, d_n)$; ③ accelerate p is slowed down randomly, $v_n = \max\{v_{n-1}, 0\}$; ④ location update, $x_n = x_n + v_n$. Numerical simulations based on these four rules reflect some traffic phenomena in reality (such as stop and go phenomenon). However, the NS model also has limitations. For example, it can only simulate single-lane traffic flow and does not allow overtaking behavior. This limits the further development of the NS model. Therefore, many scholars have extended the model to make it better conform to the characteristics of real traffic flow. The most noticeable improvement is the STCA model proposed by Chowdhury, which is famous for introducing two-lane lane changing rules that are more in line with realistic traffic flow conditions, namely

$$Cn = \begin{cases} 1 - Cn & d_n < \min\{v_n + 1, v_{max}\}, \\ & d_{n,other} > d_n, \\ & d_{n,back} > d_{safe} \\ Cn & \text{other} \end{cases} \tag{1}$$

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(1) In the formula: d_n, $d_{n,\ other}$, $d_{n,\ back}$ are the distance between the n th car and the vehicle in front, the distance between the vehicle in front of the adjacent lane, and the distance between the vehicle behind the adjacent lane; is the safe change defined in the model. Lane spacing, in the STCA model, $d_{safe} = v_{max}$; C_n is t d_{safe} he lane where the nth car is located, and $C_n = 1$ or 0. $d_n < \min(v_{n+1}, v_{max})$ indicates that the nth car is blocked in the original lane; $d_{n,\ other} > d_n$ indicates that the blocked vehicle can reach a faster speed in the other lane; $d_{n,\ back} > d_{safe}$ indicates that if the lane is changed , The safe lane change distance meets the conditions, that is, in another lane, the vehicle behind it has a certain distance.

3.2 Lane change process

Smart cars can detect the speed, position and other information of the vehicle. They can perform lane-changing processes by cooperating with the deceleration of the preceding vehicle, and provide more convenient lane-changing conditions during the lane-changing process. In this section, the lane-changing vehicle is called the vehicle in front, and the vehicle after the lane-changing is called the rear vehicle.

The discussion is based on the four situations in the first section:

1) The car in front is a manually driven car and the car behind is a smart car

In a manually driven car, the driver changes lanes, based on experience and a rough grasp of the speed of the following vehicle, and then changes lanes, because the driver cannot be prepared to determine whether the following vehicle is a smart car. In other words, as long as the vehicle in front is a manually driven car, regardless of the type of vehicle behind, the driver's habits must be considered. In the case that the front car and the rear car are both manually driven cars, the lane-changing conditions are equivalent to the smart car in this situation.

As long as the vehicle in front is a manually driven car, the lane changing conditions are the same as the two-lane lane changing conditions in the STCA model.

2) The car in front is a smart car and the car behind is a manually driven car

The smart car can read the speed and position information of the following car. The following car cannot know the next move of the preceding car, so it is equivalent to not responding at this moment. The conditions for a smart car to change lanes safely are

$$C'_i = \begin{cases} 1 - C'_i & v_i + x_i > v_j + x_j, \\ & d_{i,j\text{-}1} >= d_i, \\ & d_i < \min(v_{i+1}, v_{\max}) \\ C'_i & \text{other} \end{cases} \tag{2}$$

The main difference between the lane-changing conditions of smart cars and manual-driving cars is the safe distance for changing the vehicle. In formula (2), in addition to the same place as the STAC lane-changing rules, there is also a change in the safe distance. The smart car can calculate the specific location that the next car will reach in the next step, so that it can change lanes faster while ensuring safety.

3) Both the front car and the rear car are smart cars

When both the front car and the following car are smart cars, the following car can decelerate in advance in accordance with the lane changing behavior of the preceding car.

$$C'_i = \begin{cases} 1 - C'_i & d_{i,j\text{-}1} >= d_i, \\ & d_i < d\min(v_i + 1, v_{\max}) \\ & d_{i,j} >= v_j + v_i - \frac{1}{2}a(\Delta t)^2 \\ C'_i & \text{other} \end{cases} \tag{3}$$

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However, the deceleration of the vehicle behind will slow down the overall speed of the vehicle behind, so there is a criterion for determining if there is no mandatory lane change. Equation (3) selects the comparison of the sum of the speed of the two vehicles at the next time and the previous time after the lane change as the judgment condition.

3.3 Speed up the process

Under normal circumstances, a manually driven car will drive as fast as possible while ensuring safety. If there is no other vehicle within a safe distance ahead, the driver will choose to accelerate at this moment. As shown in the following formula (4)

$$vi(t+1)=min(vi(t)+1,v\,max) \tag{4}$$

There is a vehicle within a certain distance in front, and during the acceleration process of the vehicle in front, the driver will follow the vehicle in front to accelerate as fast as possible, but as the driver cannot know the exact value of the speed of the vehicle in front, the driver Acceleration can only be judged roughly, and there will be differences depending on the driver's judgment, so a parameter λh is added. Equation (4) is replaced with

$$v_i(t+1)=min(v_i(t)+1,v_{max},x_{i-1}-x_i-g_{safe}+v_{i-1}(t)*\lambda_h) \tag{5}$$

Among them, the accuracy of λ_h on the judgment coefficient of the preceding vehicle is taken as (0.9, 1.1) in this paper. Smart cars can obtain speed and position information, so there is no need to consider λh. Integrate the acceleration process of smart cars and manually driven cars.

3.4 Deceleration process

First define the deterministic deceleration rule. If the speed $V_k(t)$ of the K-th vehicle at time t is greater than the sum of $D_k(t)$ and the estimated vehicle speed $\lambda V_{k-1}(t)$, then a deterministic deceleration is forced, that is, when $V_k(t)>D_k(t)+\lambda V_{k-1}(t)$, set $V_k(t)=D_k(t)+\lambda V_{k-1}(t)$.

It is easy to know that when $\lambda=0$, the above rule is the deterministic deceleration rule in the classic NaSch model. At this time, the driver's driving psychology is relatively safe, and his deceleration behavior only considers the distance between him and the preceding vehicle, and ignores the driving speed of the preceding vehicle. When the safety parameter $\lambda>0$, when deciding whether to slow down, the driver will not only consider the limitation of the distance between vehicles, but also estimate the speed of the preceding vehicle to a certain extent; as the safety parameter λ increases, the driver’s driving The more risky the mind is, the higher the estimation of the speed of the vehicle ahead. When $\lambda=1$, the driver's driving psychology is very risky. Only when he thinks he will collide with the vehicle in front, he will take deceleration measures, otherwise he will continue to drive. In fact, $\lambda=0$ is not the safest driving psychology. When $\lambda=0$, since the speed of the preceding vehicle is not considered, once the following vehicle takes deceleration measures, its speed will directly decelerate from $V_{ik}(t)$ to $D_{ik}(t)$. This sudden speed reduction means a great deceleration, which not only violates the characteristics of the vehicle itself, but also easily causes rear-end vehicles to rear-end and cause traffic accidents in reality. Therefore, in order to ensure the safety of deterministic deceleration, the value of parameter λ should be a smaller value greater than zero. Compared with smart cars, the value of λ can be relatively small.

$$\begin{cases} v_i(t+1)=\min(v_i(t)+1,v_{\max},x_{i-1}-x_i-g_{safe}+v_{i-1}(t)*\lambda_h) & \text{i：manual car} \\ v_i(t+1)=\min(v_i(t)+1,v_{\max},x_{i-1}-x_i-g_{safe}+v_{i-1}(t)) & \text{i：smart car} \end{cases} \tag{6}$$

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3.5 Random slowdown

Random slowdown is common in traffic systems.

P is the random slowing down probability of the vehicle speed, that is, reduce the speed by one unit with the probability P. The existing NS model uses a fixed P value. In fact, the random slowdown probability of the speed will be appropriately adjusted according to historical experience and the current traffic environment during the driving process, which is an effective use of memory knowledge. Therefore, the random slowdown probability of the vehicle becomes if $gap_n(t) \le v_{max}$ and $v_n(t) \ge v_{n-1}(t)$, then

$$P(t+1)=\min\{P(t)+\beta(1-P(t)), P0\} \tag{7}$$

Otherwise

$$P(t+1)=(1-\alpha)P(t) \tag{8}$$

Above, P_0 is the initial slowing down probability of the vehicle, P_t is the probability of the vehicle decelerating at time t (slowing down probability), α is the memory parameter of the driver's last random slowing down probability during deceleration, and α=0 means the driver Fully remember and adopt the slowing down probability of the previous time step during driving. α=1 means that the driver completely forgets the slowing down probability of the previous time step during driving and sets the slowing down probability of this time to 0, β is the driving process of the driver For the memory parameter that does not occur random slowdown, β =0 means that the driver completely forgets the probability that the previous time step does not occur random slowdown, and β =1 means that the driver completely remembers the probability that the previous time step does not occur random slowdown. Both the probability of random slowing down at the previous time step and the probability of no random slowing down have a memory effect. When faced with a relatively relaxed driving environment, the memory effect reduces the probability of random slowing down; conversely, the memory effect does not reduce the probability of random slowing down.

Among them, when α=β=0, the above slowdown probability is the random slowdown probability in the NS model. There is no random slowing process for smart cars.

3.6 Location update

This model adopts the constant time headway strategy. In the above parameters, the distance unit is cell; the time unit is s; the speed unit is cell/s.

$$xi(t+1) = xi(t) + vi(t) \tag{9}$$

4. Data simulation analysis

In this paper, a two-lane road with a length of 3km is discretized along the driving direction. Each cell has a length of 3m, and each lane has a total of 1000 cells. Each vehicle has a length of 6m and occupies two cells each time. Take the random slowdown probability as 0.3. The vehicle acceleration is 3m/s2, the maximum speed is 15m/s, which is 5cell/s, and the simulation step is 1s. Each iteration is 1 h, that is, 3600 time steps (s), and the previous 2600s are excluded to achieve a stable state as a whole. It is worth noting that within 1 s of each time step, the CA model is updated once and the state of the smart car needs to be updated 10 times, that is, the smart car perceives the state of the traffic system every 0.1 s and realizes its own running speed and position according to the car following model. For the update of the manual driving car, the speed is kept constant, and the position information is obtained through linear interpolation. Simulates the mixed traffic flow operating condition based on the cell model. In the simulation, a traffic flow of 3cell/s is also added, which accounts for 5% of the total number of vehicles.

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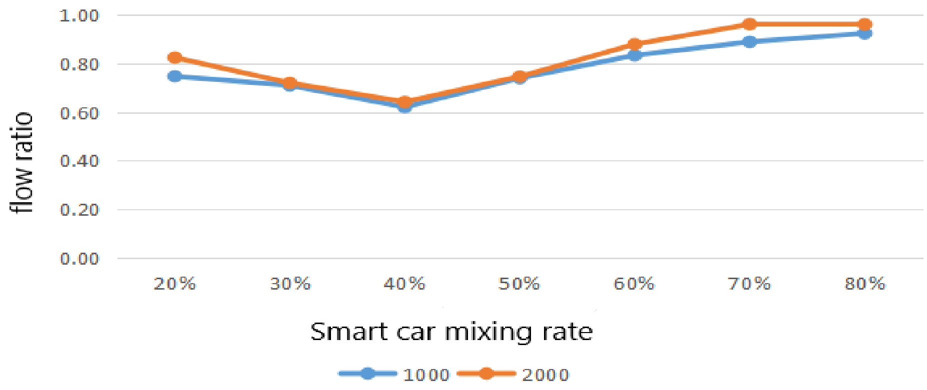

Fig. 3 The impact of different smart car mixing rates on traffic

As shown in Figure 3, the mixing rate of smart cars ranges from 20% to 80%. From this simulation result, it can be roughly seen that as the mixing rate of smart cars increases, the ratio of the flow rate to the total number first increases and then decreases (the flow rate ratio in the figure is the fixed value of the final outflow rate ratio and then the same the ratio of total traffic). About 40% of the smart car mixing rate will be the mixing rate most affected by the main traffic flow, making the traffic flow the largest. It is similar to the results in [7].

5. Conclusion

Based on the cellular automaton model, this paper studies the mixed traffic flow mixed into intelligent vehicles to adapt to the situation of mixed into intelligent vehicles. The simulation results are similar to other documents. However, there are still some problems, such as too few simulation verification data, unable to find the corresponding examples in reality, and the random slowdown probability needs to be further verified when it is mixed into the smart car.

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