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The Assessment of Traffic with Self-driving, Cooperating Cars

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Abstract. Based on the NaSch traffic model, we propose a mixing traffic flow model for a multilane system. In this model, the characteristic of Self-driving, Cooperating Cars are abstracted as rules, to make the traffic model can be applied to the traffic with Self-driving, Cooperating Cars. Through the simulation in the model, we found that the Self-driving, Cooperating Cars have a great influence on the capabilities of expressway, and have a decisive action on waiting time before traffic light.

1. Introduction

Self-driving, cooperating cars are developed rapidly in recent years. With the characteristics of rational driving habits, fast control ability and fully grasp the road information, self-driving, cooperating cars is considered having the potential to alter transportation systems [1]. However, the characteristic of these cars is not well understood at this point. In this paper, author uses mathematical model to analyze the flow of mixed traffic.

In the theory of traffic flow, Cellular Automata (CA) model can simulate the microscopic behavior effectively. The existing models for analyzing traffic situation in CA can be divided into single-lane model and multi-lane model [2]. In single-lane model, Nagel presented a simple one-dimensional traffic model: $v_{t+1} = \min\{v_t + 1, v_{\max}\}$, $v_n = \min\{v_n, d_n - 1\}$, $x_n = x_n + v_n$. Further, the NaSch model takes the random factors into consideration, introducing the Stochastic slowing down factor *p*. Then, the VDR model considers the relationship between the *p* and the vehicle speed in the NaSch model, and makes a good reflection of the metastable state in the real traffic flow. In addition, the FI model is discussed for the application of acceleration and deceleration rules for vehicles and the WFW model takes the driver's judgment of the speed of vehicle ahead into account when driving at a high speed. Based on single-lane model, the multi-lane model can be established by adding the lane changing rules. Cremer first studied the lane changing rules based on the speed of the front vehicle and the target lane neutral. In the paper written by Rickert, the lane changing model takes the symmetry, the random factors and the characteristics of the front and rear cars in lane changing into consideration, and proves that the backward observation is a key factor in building the lane changing model. In addition, considering the traffic rules in Germany, Wanger has established a multi-lane model with the least number of brakes and less interfere with other rear car, which reflect many aspects of the actual traffic in Germany. Moreover, Nagel has introduced three criteria in lane changing model: safety, traffic regulations and travel time, which proved helpful to produce a real traffic flow model.

2. Model

2.1 The Analysis of Self-Driving, Cooperating Cars

The behavior of formation convoy in self-driving, cooperating cars provides vehicle a safe, predictable and fast driving condition [3]. The navigation based on the communication can help the vehicle master enough path information to make a better driving route [4]. To analyze microcosmic behaviors of vehicles, the feature of self-driving, cooperating cars such as convoy and navigation are extracted as rules in the CA model to describe the mixed traffic flow.

2.2 The Rule for the Mixing Traffic Flow

2.2.1 Driving Model of Regular Cars

The distance and relative speed between the car and the front one are taken into consideration in accelerating and decelerating. Combining NaSch model and WFW model, we propose the rule of acceleration and deceleration.

Acceleration: $\Delta v_n = \gamma.\frac{gap_n - d_{safe}}{\Delta t} + (1-\gamma)(v_{n-1} - v_n)$, $v_n = \min\{v_n + \Delta v_n, v_{\max}\}$ (1-1)

Deceleration: $v_n = \min\{v_n, \gamma gap_n + (1-\gamma)(v_{n-1} - v_n)\}$ (1-2)

By making a further improvement on Nagel lane changing model, considering safety, speed limited by traffic regulations and the shorter time of driving, the rules of lane changing are defined as follows. The two-lane model is extended to multi lane model by the rule as follows:

$$\text{Turn to the left lane}\begin{cases} gap_n < \min\{v_n+1, v_{\max}\} \\ gap_{n.FL} > gap_n \\ gap_{n.FL} > gap_{n.FR} \\ gap_{n.BL} > gap_{safe} \end{cases} \quad \text{Turn to the right lane}\begin{cases} gap_n < \min\{v_n+1, v_{\max}\} \\ gap_{n.FR} > gap_n \\ gap_{n.FR} > gap_{n.FL} \\ gap_{n.BR} > gap_{safe} \end{cases} \quad (2)$$

When the left and right channel conditions are satisfied at the same time, the channel change to the left is preferred.

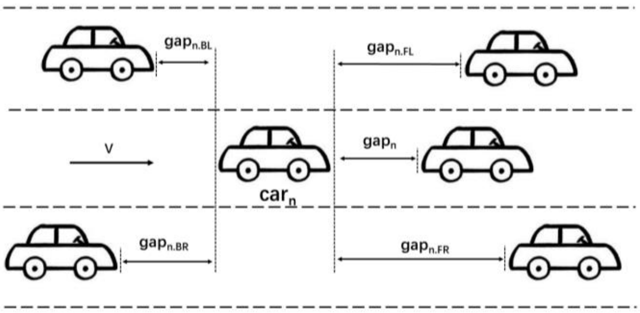

Fig.1 A sketch map of changing lines

In this model, x_n is the place of the N*th* car ,v_n is the velocity of the N*th* car,gap_n is the distance between the the N*th* car front car, v_{max} is the limit velocity,γ is the coefficient between 0 and 1. Other paraments are illustrated in Fig.1.

2.2.2 Driving Model of Regular Cars

Rules for basic driving: Acceleration and deceleration

For radar system and high speed sensor, self-driving, cooperating cars can judge the gap and speed accurately. It helps to apply consistent acceleration and deceleration rates with the optimistic use of gap. Considering the upper limit of acceleration: $x_n' - x_{n-1}' - l_n - l_{n-1} > d_{safe}$, its acceleration and deceleration can be defined by the equations below:

$$\Delta v = v_{n-1} - \frac{d_{safe}' - gap_n}{\Delta t} - v_n \quad (3\text{-}1)$$

Hence, the acceleration process can be described as:

$$v_n = \min\{v_n + \Delta v_n, v_{\max}\} \quad (3\text{-}2)$$

Rules for cooperation: Forming convoys

Convoys can help cars share the information with the front one such as position, speed, acceleration in time, which can help cars start, stop more quickly.

Step one: Approaching the front self-driving, cooperating car.When operating, self-driving, cooperating car can detect whether the front car is the same. If it is, the later could drive at a larger acceleration without crashing into the front one by knowing the speed, position and the driving plan of the car. In this case, the state of motion can be concluded as the formula (3-1) and (3-2).

Step two: Forming convoys.When the length of gap between the cars is less than the safe distance, the cars could forming convoys. Once forming convoys, the behind one will drive at the same speed and acceleration of the front one till the different driving routes set them apart.

Forming convoys can simplified by mathematical linguistics as $\Delta v_n = \Delta v_{n-1}, v_n = v_{n-1}$ (4)

Rules for navigation: changing lanes

According to the surroundings, human drivers choose the plan of changing lines. By mastering more information, self-driving, cooperating cars can have plenty of time to plan the routes in advance. The advanced plan reduces the time wasted in the crowded road when changing lanes.Therefore, we can use the formula (5-1)and(5-2) below replace the formula merely associated with surrounding vehicles in formula (2).

$$(1-p)(gap_{n.FL} - gap_n) + p(\rho - \rho_L) \tag{5-1}$$

$$(1-p)(gap_{n.FR} - gap_n) + p(\rho - \rho_R) \tag{5-2}$$

ρ is the Vehicle density in a lane which reflect the congestion of the lane. p is a coefficient between 0 and 1. Obviously, the greater the p, the more cognition about the traffic, make the better decision when changing lane.

3. Stimulation and Conclusion

The impact of self-driving cooperating car on traffic is analyzed separately combined with the of features urban and expressway traffic.

3.1 The Simulation Under the Urban Road Features

Urban traffic is characterized by a large density of vehicles, shorter sections, lower speed limits, and often use traffic lights at intersections. In the urban road, the driver is concerned about the time of crossing the road, and the traffic management department is concerned about how much traffic the road can take in rush hour. Therefore, the average waiting time before traffic lights and the maximum traffic are selected as index to study the influence of the self-driving cars on the urban road traffic.

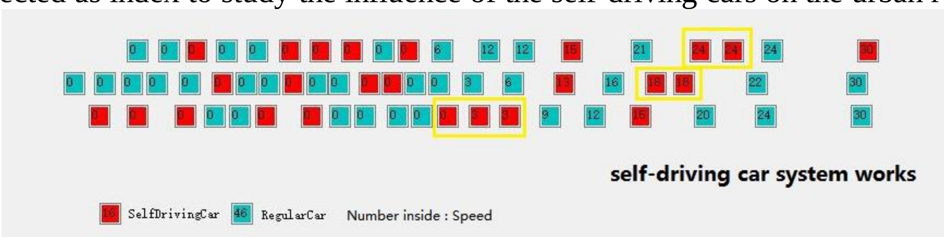

Fig.2 immediately start

Since the information sharing system can help cars master the information about the front one in time, which includes positions, speeds, etc. This information can help cars start, stop more quickly. Which play a huge advantage after the waiting of traffic light.

Changing the number of lanes, length, vehicle density, we calculate the average of the vehicle starting time and low speed time in different situations, and explore the relationship with the percentage of self-driving cooperating car. The results are as follows:

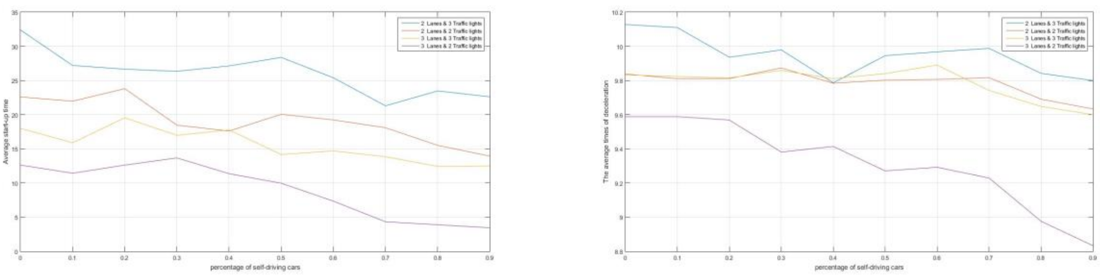

Fig.3 relationship between p and average start-up time and average times of deceleration

From the results, the following conclusions can be reached.

With the increase of the proportion of Self-driving, cooperating car, the two indicators have a downward trend in the same situation. When the percentage of self-driving, cooperating cars is greater than 60%, the start time can be reduced by 30%.

Although the proportion of self-driving, cooperating car has a certain positive impact on the efficiency of urban road traffic, the road's capacity is still an important factor for the urban traffic.

3.2 The Simulation Under the Expressway Features

Expressway traffic is characterized by low traffic density, long section and small impact of the ramp. In the expressway, drivers concern about the average driving speed, and the manager concerns about the road capacity. Therefore, the vehicle speed and traffic flow are selected as index to explore the impact of the self-driving cars on the expressway traffic. The same calculation is taken as before.

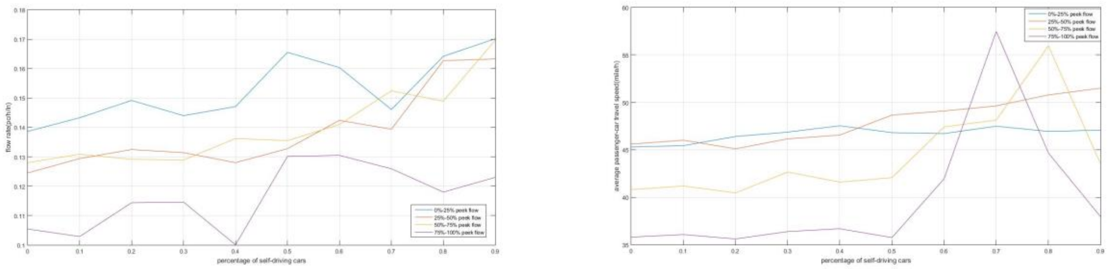

Fig.4 relationship between p and flow rate, average speed

From the results, the following conclusions can be reached:

When the traffic is in the general level, there is a positive effect on the traffic condition when the proportion of self-driving cars improves. Especially when the proportion is higher than 50%, the traffic capacity rises significantly, which can be up to about 55%. The cooperation and navigation ability of self-driving, cooperating cars greatly impacts the system.

When the traffic is large, the negative influence begins to show. For example, while the proportion is over than 80%, traffic efficiency declines for that the great amount of self-driving, cooperative cars have formed a scale of obstacles in different lane, just like some mobile blocking wall, which greatly affects the turning and lane changing.

Fig.5 the mobile wall

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