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The Impact of Self-Driving Cars on Existing Transportation Networks

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Abstract: In this paper, considering the usage of self-driving, I research the congestion problems of traffic networks from both macro and micro levels. Firstly, the macroscopic mathematical model is established using the Greenshields function, analytic hierarchy process and Monte Carlo simulation, where the congestion level is divided into five levels according to the average vehicle speed. The roads with an obvious congestion situation is investigated mainly and the traffic flow and topology of the roads are analyzed firstly. By processing the data, I propose a traffic congestion model. In the model, I assume that half of the non-self-driving cars only take the shortest route and the other half can choose the path randomly. While self-driving cars can obtain vehicle density data of each road and choose the path more reasonable. When the path traffic density exceeds specific value, it cannot be selected. To overcome the dimensional differences of data, I rate the paths by BORDA sorting. The Monte Carlo simulation of Cellular Automaton is used to obtain the negative feedback information of the density of the traffic network, where the vehicles are added into the road network one by one. I then analyze the influence of negative feedback information on path selection of intelligent cars. The conclusion is that the increase of the proportion of intelligent vehicles will make the road load more balanced, and the self-driving cars can avoid the peak and reduce the degree of road congestion. Combined with other models, the optimal self-driving ratio is about sixty-two percent. From the microscopic aspect, by using the single-lane traffic NS rule, another model is established to analyze the road Partition scheme. The self-driving traffic is more intelligent and their cooperation can reduce the random deceleration probability. By the model, I get the different self-driving ratio of space-time distribution. I also simulate the case of making a lane separately for self-driving, compared to the former model. It is concluded that a single lane is more efficient in a certain interval. However, it is not recommended to offer a lane separately. However, the self-driving also faces the problem of hacker attacks and greater damage after fault. So, when self-driving ratio is higher than a certain value, the increase of traffic flow rate is small. In this article, that value is discussed and the optimal proportion is determined. Finally, I give a nontechnical explanation of the problem.

Keywords: macroscopic mathematical, BORDA, Cellular Automaton, negative feedback, microscopic.

1. INTRODUCTION

With the increase in the number of vehicles, urban transport system is becoming more and more developed and complex. However, the number of roads will not unrestrictedly grow to meet the needs of motor vehicles. Therefore, the city will have the need to increase the volume of traffic with the limited capacity of the road network design. In the Seattle area of the United States, for example, congestion at the peak of a traffic jam, due to these contradictions, is very serious. Especially in the No. 5, No. 90 and No. 405 Interstate Highway and Highway No. 520, the traffic delay problem is more obvious. In the program I study in this paper, I use the self-driving cars and their cooperation to increase the road transport capacity, without increasing the number of lanes and road conditions.

The so-called self-driving car can be completely separated from the control of people and be driven only under the command of the computer. Its ability to travel independently comes from artificial intelligence, visual computing and other technology collaboration.

Theoretically speaking, self-driving vehicles have more perception of the environment than human, so its response to potential crises is more rapid than human driving. It can also avoid traffic accidents caused by short driving distance, distracted driving, dangerous driving and other human factors and reduce the safety gap required for traffic. It is conducive to the management of traffic flow and the reduction of traffic jam. The first truly autonomous cars, capable of driving without any human intervention, appeared in the 1980s, being results of pioneering research work conducted by the team of E. Dickmann (Mercedes-Benz van with cameras, sensors and sophisticated computer vision strategies, Dickmann and Zapp (1988)) and, independently, by the team from Carnegie Mellon University (projects NavLav and Autonomous Land Vehicle, Kanade et al. (1986)). Even these first approaches, designed in the era of computers with loIr computational poIr than nowadays, Ire based on very advanced tools and concepts, such as lidar (remote sensing technology which measures distance by illuminating a target with a laser and analyzing the reflected light) [1], transputer (microprocessor designed for parallel processing), Kalman filters, neural networks. Nowadays, many major automotive manufacturers are testing driverless cars technology. Also, IT companies (e.g., Google (2015), Apple (2015)) and research institutes (e.g., VisLab (2015), Oxford University (2015), FUM (2015)) are working on their models of self-driving vehicles, including also electric poIr supply. In some U.S. states (e.g., Nevada, Florida, California, Michigan) autonomous cars are already permitted (NCSL (2015), UoW (2015)). Some other countries have alloId testing autonomous cars in traffic as Ill. There are interesting projects aiming to demonstrate autonomous vehicles potential, e.g., CityMobil2 (2015), Beta City Initiative (2015). [2]

2. ORGANIZATION OF THE TEXT

2.1 Model one

2.1.1Analysis of Seattle Road Congestion Degree

$$\mathbf{F} = \boldsymbol{\rho}\mathbf{v}. \tag{1}$$

$$\boldsymbol{\rho} = \frac{F}{v}. \tag{2}$$

Based on the information given, I learn that there are many congested roads in the Seattle area because traffic volumes exceed the design capacity of the road network. I will focus on the 5, 90, 405 and 520 roads.

I get the table of the congestion degree. After analyzing the congestion degree of all the roads in Seattle, I determine the level two as the judge. In the histogram, the statics that are over the blue line belong to the road that will be crowded during traffic peak time. This kind of roads accounts for 42.6% in all. This way, I can determine the general congestion of this area.

Table 1. Congestion rating scale

Crowded ranking	The percentage of maximum speed	Vehicle density(veh/km)	Single channel per hour Vehicle flow(car)	Human feelings
I	90%~100%	0~25	0~2173.5	Feel free
II	80%~90%	25~50	2173.5~3864.0	Feel relax
III	70%~80%	50~75	3864.0~5071.5	Feel pressure
IV	60%~70%	75~100	5071.5~5796.0	Feel upset
V	<60%	>125	<5796.0	Unbearable

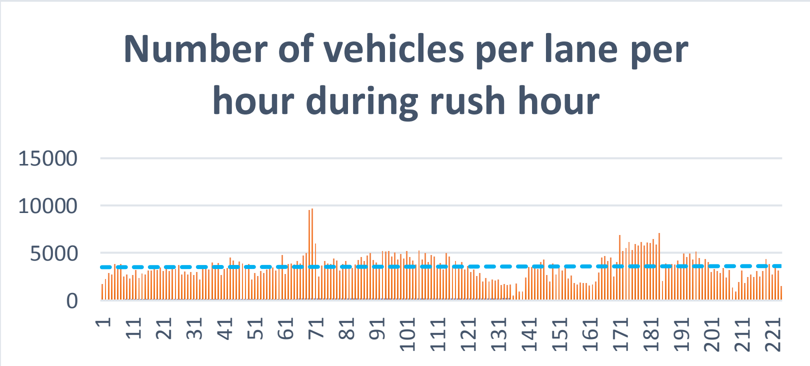


Figure 1. Frequency distribution histogram

I isolate the subject of several highways from the map for analysis. The simplified road map has a shape as shown. Suppose the starting point and the destination are the two endpoints of the graph respectively, A and B.

According to the figure, there are eight different paths between the two sites. It should be noted here that although the simplified diagram is a symmetrical geometry, the eight paths are of different lengths.

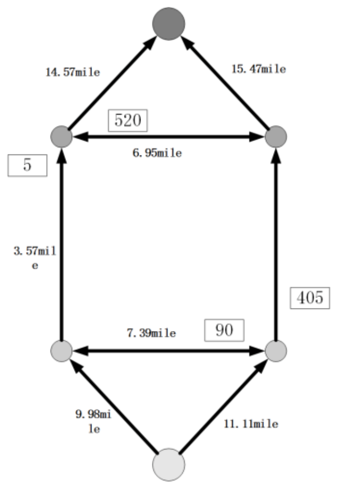
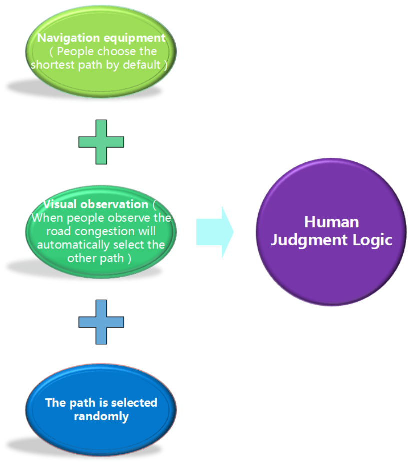


Figure 2. Simplification of the map

After I introduce the self-driving, the type of car is divided into two parts, part of the self-driving and part of the non-self-driving. When driving from point A to point B, the self-driving and the non-self-driving select paths in different ways. Because of the different preferences of the passengers in the different self-driving and several factors affecting the choice of paths, I use AHP to analyze the influence of different factors on the selection of the path of self-driving. Self-driving is affected by four factors on the choice of the road, namely, safety, time, fuel consumption and ornamental value. It should be noted here that although different vehicles are affected to varying degrees by different factors, safety first is the first criterion for driving. So, safety is always in the most important position among the four factors. [3]

When considering only cars driven by people on the road, most of the vehicles choose the shortest route recommended by the navigation, and only a small part of the vehicles choose differently from the navigation because of the autonomy and randomness of the drivers. With the addition of self-driving, the vehicle's choice of paths becomes more diversified.



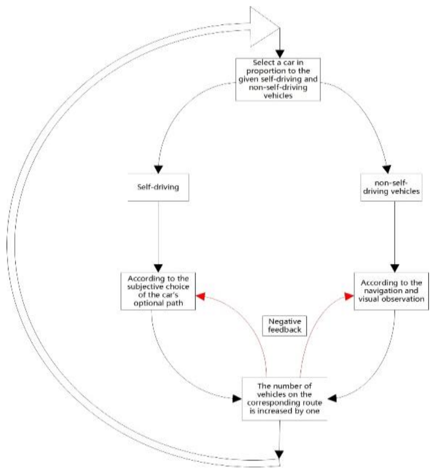


Figure 3. Driving judgement of people

Figure 4. Schematic diagram of model

1

The following describes how the self-driving and non-self-driving cars select the path.

2.1.2. Analytic hierarchy process

In the four dimensions, respectively, sort the eight roads according to the quantitative results, and assign them to the serial number 1-8. The larger the number of the road is, the better advantage the path takes in this dimension. For example, in the time dimension, the route with sequence number 8 takes the shortest time. Next, as I consider, the degrees how self-driving cars care for each of the four factors are different. That is, four factors in different self-driving cars stay in different order. And security is always ranked first. I can know that, from the permutation and combination of knowledge, there are six of this sort. [4]

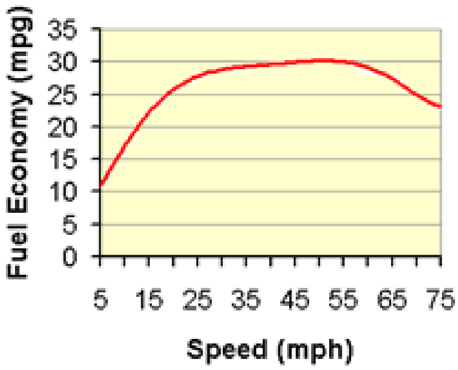


Figure 5. The relationship between speed and fuel consumption of ten miles per

Table 2. Fuel price relationship

v/(mile/h)	60	55	50	45	40	35	30	25
$	$0.58	$0.64	$0.70	$0.78	$0.88	$1.00	$1.17	$1.40

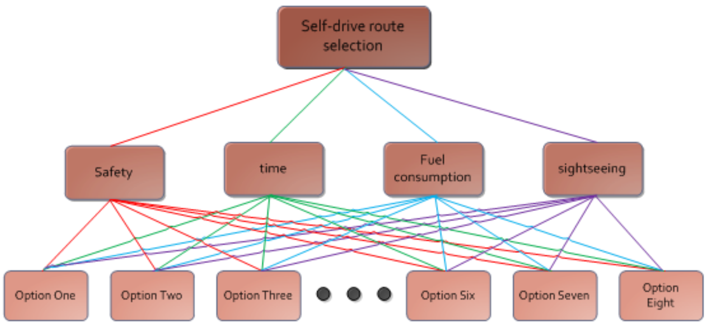


Figure6. A hierarchy of self-driving route selection

Next, I use the Analytic Hierarchy Process (AHP) [5] to calculate the Iights of the four factors. I randomly select a situation to calculate. Here is the calculation process:

The Iight matrix is:

Correlation matrix= $\begin{bmatrix} 1 & 3 & 5 & 8 \\ \frac{1}{3} & 1 & \frac{5}{3} & \frac{8}{3} \\ \frac{1}{5} & \frac{3}{5} & 1 & \frac{8}{5} \\ \frac{1}{8} & \frac{3}{8} & \frac{5}{8} & 1 \end{bmatrix}$

When comparing the importance of the i-th element and the j-th element with a certain factor above, I describe it by the relative Iights aij which is quantified. If there are total of n elements in the comparison, the pairwise comparison matrix comes like $\mathrm{A} = (a_{ij})_{nxn}$.

Here, I make a 4 * 4 matrix with the four elements in order being safety, time, fuel and ornamental value.

The value of aij in the pairwise comparison matrix is defined as follows:

$a_{ij} = 1$;

Element i and element j have the same importance compared with the upper level factor.

$a_{ij} = 3$;

Element i is slightly more important than element j.

$a_{ij} = 5$;

Element i is more important than element j

$a_{ij} = 7$;

Element i is much more important than element j

$a_{ij} = 9$.

In the matrix, a11 stands for the importance of "safety" versus "safety"; a12 for "safety" versus "time"; a13 for "safety" A14 represents the importance of "security" relative to "ornamental value"; a21 represents the importance of "time" relative to "security", and so on.

Finally, the matrix is calculated as the Iight of the four factors. The Iight of the Iight a = 0.6030; the time Iight b = 0.2010; the Iight of the fuel quantity c = 0.1206; the Iight of the ornamental value d = 0.0754.

Table 3. The Iight of each factor in each case

1	Safety	time	Fuel consumption	sightseeing	2	Safety	time	sightseeing	Fuel consumption
weight	0.6030	0.2010	0.1206	0.0754	weight	0.6030	0.2010	0.1206	0.0754
percentage	60.30%	20.10%	12.06%	7.54%	percentage	60.30%	20.10%	12.06%	7.54%
3	Safety	sightseeing	Fuel consumption	time	4	Safety	sightseeing	time	Fuel consumption
weight	0.6030	0.2010	0.1206	0.0754	weight	0.6030	0.2010	0.1206	0.0754
percentage	60.30%	20.10%	12.06%	7.54%	percentage	60.30%	20.10%	12.06%	7.54%
5	Safety	Fuel consumption	sightseeing	time	6	Safety	Fuel consumption	time	sightseeing
weight	0.6030	0.2010	0.1206	0.0754	weight	0.6030	0.2010	0.1206	0.0754
percentage	60.30%	20.10%	12.06%	7.54%	percentage	60.30%	20.10%	12.06%	7.54%

Different self-driving cars value the four factors with different degrees, so the corresponding Iight of the four factors may change accordingly. Six different results are shown in the following table.

2.1.3. BORDA count

The main idea of the BORDA [6] sorting algorithm is to sum the number of elements behind each factor in different orders and determine the sum as the score of each factor. Finally, sort the factors by scores. Our algorithm draws on this idea. In the analysis of each road, I need to calculate the score according to the following formula:

W=a*γ_{t}+ b*γ_{f}+ c*γ_{s}+ d*γ_{v}.

In the formula, a, b, c, and dare Iights of four factors arranged in order. Γt is the sort number of a certain road in the time dimension. γf is its number in the fuel volume dimension. γs is its number in the security dimension. γv is its ranking in the ornamental value dimension.
After calculation, I get the scores of each path, and select the best path of self-driving.

S: Safety point t:Travel time ρ_{max}:Maximum traffic density ρ:Traffic density f:Fuel consumption

$$S \propto \frac{1}{l}$$

$$t = \frac{L}{V_{max}(1 - \frac{\rho}{\rho_{max}})}$$

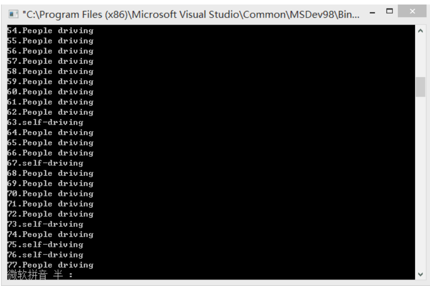
$$\rho_{max} = \frac{1}{d}$$

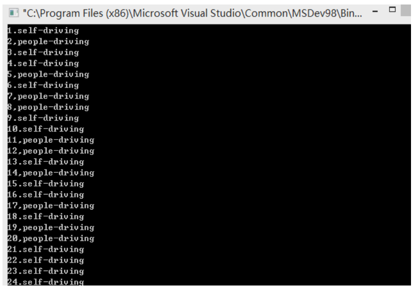
$$\rho = \frac{1}{d + l}$$

$$f \propto L$$

2.1.4. Monte carlo simulation:

In order to simulate how different types of cars choose their own path, I use the Monte Carlo simulation approach. I assume that the road is initially empty, and then put into a number of vehicles from the starting point towards the end, including self-driving and non-self-driving cars. I employ c language program to simulate and count the vehicles with various choices and form the data into a table. In the simulation, I totally put in 13,000 cars. In order to determine the different impact caused by the changing proportion of self-driving on the traffic, I have done three different procedures, with the proportion of self-driving respectively being 10%, 50% and 90%. Part of the results of the program are intercepted as follows:

10%: 

50%: 

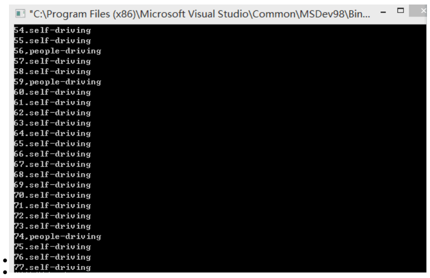
90%: 

Figure 7. There are random segments of the two vehicles under various proportions given by c++

Table 4. Path vehicle segment table based on Monte Carlo algorithm

	Option one	Option two	Option three	Option fore	Option five	Option six	Option seven	Option eight
self-driving:0%	3395	1366	1380	1324	1367	1377	1410	1421
self-driving:10%	3121	1388	1382	1507	1317	1407	1396	1522
self-driving:50%	2637	1379	1370	1704	1434	1356	1371	1789
self-driving:90%	2338	1478	1455	1625	1521	1451	1474	1698

Fit all the data with MATLAB software, and draw the curves representing different circumstances. The simulation results are as follows:

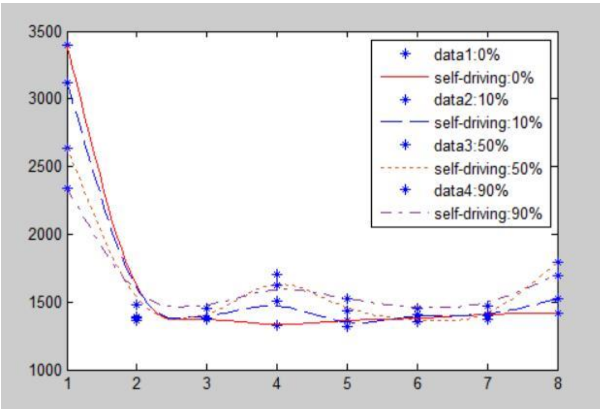


Figure 8. Sketch map of road vehicle partial curve

According to the curves above, cars driven by people are generally guided by their navigation, taking the nearest road. The vehicle throughput of other roads is much loIr than that road. With the gradual introduction of self-driving, the vehicle on road 1 significantly reduces, and that on other roads begins to increase, especially on the road 4. The curve is gentler than before. As a result, the overall congestion degree of the eight roads decreases, traffic speed inevitably increases.

2.1.5. Prisoner 's dilemma [7]

As shown in Figure 4, the first road has the highest vehicle throughput. This resembles an academic phenomenon prisoner's dilemma. The two sides in the face of the same choice, since they cannot communicate and change information, they all choose the most benefit to their own way. In the end, it causes damage to the overall interests. In this paper, the cars driven by people cannot communicate with each other, so all of them choose the shortest path to walk up their own, which is recommended by navigation. This will cause that the road traffic is much higher than the other road. Congestion is more serious.

2.2 Model two

2.2.1 One - way street NS rules [8]

The one-way NS rule is used to simulate the driving condition of a vehicle on a road. By simplification, I can come to the following five models.

Note: Each iteration goes through six steps

Figure 9. Schematic diagram of iteration with or without self-driving

Initial state: The velocity V n of the three vehicles is assumed to be V1 = 2 m /s, V2 = 1 m / s and V3 = 0 m / s.

whether to put self-driving cars

$V_n = \min(V_{max}, V_n+1)$, $V_{max}=2$ m/s.

Acceleration rules: Vn can only be added on the basis of less than or equal to 2 units

Collision avoidance: In order to prevent the car from colliding, the velocity V n can only be equal to dn-1. D n is the distance from the nose of the n-th vehicle to the rear of the (n + 1) -th vehicle.

random deceleration: each car decelerates a unit according by a certain probability P, the minimum the velocity can be reduced to is 0.

Position Update: The position of each vehicle in the next state is Xn = Xn + Vn

Theoretical analysis

First, three definitions are given.

ρ_c= Critical density

Average speed V= min (V_{max}, d)

J= min (ρV_{max},ρ d)= min(ρV_{max},1-ρ)Traffic flow

I will code the algorithm, and use MATLAB software to draw the driving situations into a map , making it seems more intuitive.

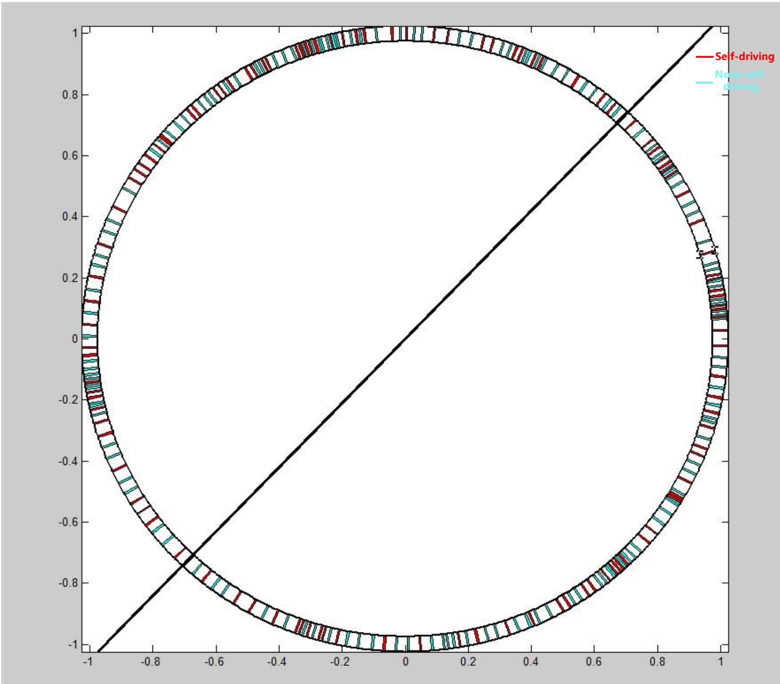


Figure 10.

Proportion of self-driving :100%

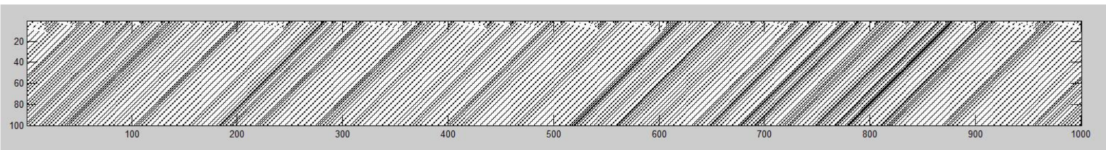


Figure 11.

Note: In the spatiotemporal map, the abscissa represents the distance, and the ordinate represents the iteration count. In this simulation, I choose to do 100 iterations in 1 km.

This chart shows that if the roads are full of self-driving cars, basically, road congestion will not be the case, and speeds are consistent.

Proportion of self-driving:90%

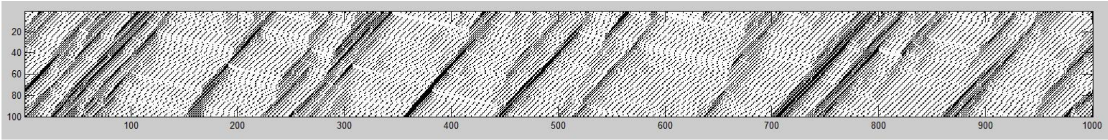


Figure 12.

Proportion of self-driving:50%

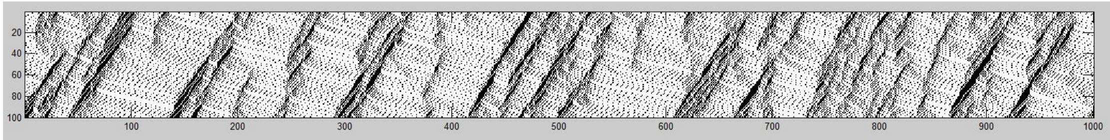


Figure 13.

Proportion of self-driving:10%

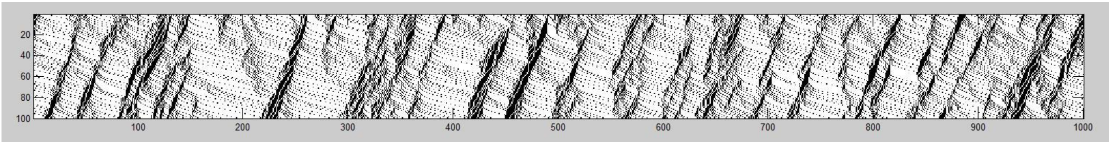


Figure 14.

When self-driving cars tail off, the crowded roads become very much and the congestion is very serious.

2.3 Select the appropriate proportion of self-driving

According to the NS single-lane rule, I simulate traffic vehicles in a certain length of road. After simulating several times, with each time only changing the proportion of self-driving, I use MATLAB to calculate the number of vehicles through a certain path after the same number of iterations. The image is as follows:

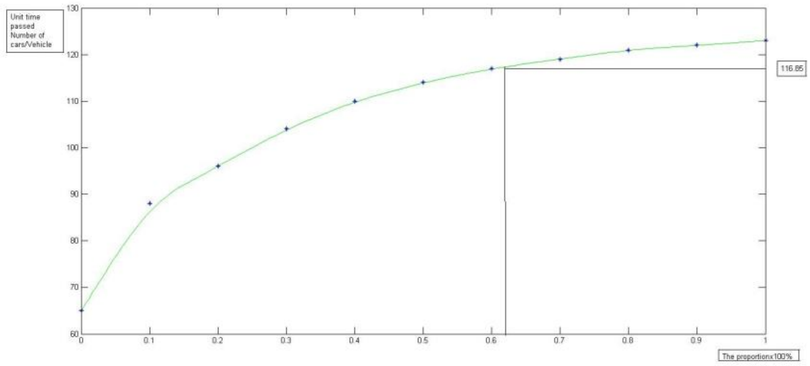


Figure 15.

Under the assumption of the model, I find that the overall traffic speed increases with the percentage of self-driving increasing, but the increase is sloIr and sloIr because I do not take the safety problem of self-driving into account. The sensitivity of the sensor is reduced when driving in rainy Iather. Self-driving software systems may also be cracked by hackers. The big proportion of self-driving cars may reduce the overall safety of the road. So, I take the **5%** of road traffic volume for the maximum tolerance range. According to the image, when the density of self-drive is 62 percent, the current road network speed has improved greatly. And the entire road safety will not drop too much.

3. CONCLUSION

I use the negative feedback model to simulate the entire transport network, and the models are established from the macro and micro levels

In the macro model part, I consider the action logic of self-driving and none-self-driving cars, and the conclusions are in good agreement with those observed in real life. I take full account of people's needs and preferences and overcome the dimensional differences with BORDA number of sorting method. The curve made through Monte Carlo simulation can be a direct reflection of practical significance of the model.

In the microscopic model, I boldly use the NS single-aisle model to analyze the characteristics of the changes of vehicles with time, and obtain a scatter gram with time iteration, which intuitively embody the concept of congestion. A deep understanding of this model allows us to freely add different proportions of self-driving cars to derive the spatiotemporal maps I need. Each of steps follows the assumptions of the model and gives results with strong regularity. The accuracy of the model has also been confirmed.

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