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Article

Macroscopic and Microscopic Analysis of Chinese Typical Driving Behavior from UAV View

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Abstract: For improving the performance of ADAS and AD system in China, the driving behavior of Chinese drivers is being increasingly focused. The purpose of this study is to investigate the macroscopic and microscopic characteristics of typical Chinese driving behavior, by using UAV to capture and extract them. Traffic flow rate, traffic density, velocity, acceleration and offset from the lane center were acquired and their influence by the vehicle types and lane types studied. Minimum TTC and THW during lane changing and car following and their influence by following types and lane types were also studied. Results showed that the Chinese traffic state was more stable than in Germany, however, with more aggressive behavior, compared to HighD. The entire velocity was small due to strict speed regulation in China. Different characteristics were found for different vehicle types, following types and lanes. Car and car-car following showed more dangerous potential. Cars tended to drive left and trucks tended to right of the lane center. Conclusions can be made that Chinese driving behavior is largely different from German driving behavior. These driver characteristics in China provided data support for the training of an AI-based decision algorithm, development from a localized system and design of roads.

Keywords: Chinese driving behavior; big data; UAV view; road safety

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1. Introduction

Driving behavior analysis from macroscopic and microscopic point is an important topic for pushing forward the localization of Intelligent Connected Vehicles. Knowing them in different angles is beneficial for both enhancing the safety of automated vehicles and the efficiency of the whole traffic.

Naturalistic driving datasets from data acquisition vehicles were commonly used in driving behavior analysis. The U-DRIVE project in Europe and SHRP2 project in the US have collected naturalistic data for more than one million km [1,2], and CAERI and Tongji University in China have collected either [3,4]. Typical behavior, such as free driving, car following, lane changing and overtaking, were analyzed and control models were built [5–7]. These data were applied in the development for ADAS systems like ACC [8], AEB [9], LKA [10] and APS [11], also in the investigation for deep learning based AD system [12]. However, the influence of macroscopic traffic characteristics was difficult to reveal while analyzing driving behavior only using vehicle-based data acquisition equipment.

Bird view data were recently collected and used for driving behavior analysis, such as HighD [13] and NGSIM dataset [14]. The former one collected more than 17 h video on a major German highway using UAV and the latter one collected 90 min video using a monitoring camera in the US. Compared to NGSIM, HighD has higher precision so it was widely used. Friedrich Krube et al. made a macroscopic and microscopic analysis for HighD [15] and Valentina Kurtc calibrated two cars following a model based on it [16]. Vishal Mahajan et al. analyzed the crash risk due to lane changing and quantified them by weighing the likelihood by the potential severity of a collision [17]. Rongjie Yu [18] established a high-risk event prediction model in the highway and analyzed the affecting factors. Zheng et al. established the intelligent vehicle risk assessment method and driving behavioral decision making model and calibrated them using HighD data [19,20]. These studies have helped with the understanding of driving behavior, however, more concentration is needed on China.

To better understand Chinese driving behavior, bird view data were used recently. Xue et al. [21] collected normal traffic flow in two intersections and developed an automated danger behavior detecting algorithm using machine learning method and six hundred extracted vehicle trajectories. Ma et al. [22] performed a safety analysis for lane changing behavior based on highway driving data using two UAV joint collection technologies. Gu et al. [23] established a merging behavior model through the crash risk analysis of mandatory merging manoeuvers in the interchange merging area. Compared to naturalistic driving data, few UAV data were collected so it was difficult to describe the typical behavior affected by the traffic.

Differences commonly exist in driving behavior in various ways due to driving culture [24]. Tong Liu and Selpi compared the car following behavior between China and Sweden through track test [25]. Hussain et al. analyzed the Asian driving behavior of abnormal drivers, and a difference was found in the similar geographical region [26]. Zhao et al. [27] calibrated the algorithm developed by a foreign manufacturer using typical Chinese driving characteristics acquired from the vehicle based data, and the decrease in efficiency was observed. Therefore, it is necessary to collect more driving data, especially the bird view data, for improving the adaptability of ADAS or AD system to native drivers.

This study firstly collected the Chinese typical driving behavior in highways using UAVs. Then macroscopic and microscopic analyses for traffic flow rate, traffic density, velocity, acceleration, TTC, THW were performed. The difference between vehicle types, driving lanes and countries were also investigated.

2. Materials and Methods

Six highway sections in Guangzhou and Shanghai were selected for data collection, with three straight driving lanes and one emergency lane in each direction. About 17 h videos were acquired and the lane length was about 400 to 420 m. DJI Phantom 4 pro V2.0 were used and 4K resolution video with 30 fps were captured. One drone was flying directly above the highway section. All videos were shot between 8 a.m. and 6 p.m., while the weather was clear and the road surface was dry.

The drone is able to automatically decrease the vibration, although inevitable rotation still exists, due to wind in the sky. Deep learning methods were often used when performing vehicle detection and classification [28,29]. In this study, the trajectory generation workflow was shown in Figure 1, combing several deep learning methods. Relactive rotation was corrected using SURF and FLANN method, while the former one extracted the feature point and the latter one matched them [30]. The relative rotation between other frames and the first frame were then aligned to the first one. The absolute rotation of the first frame was manually recorded and corrected for each video, then they were adjusted to absolute horizontal position. We leveraged the concept of Transfer Learning for Deep Neural Network (DNN) to re-purpose well bench-marked DNN models to detect small objects of cars with a "Bird's Eye View" instead of "Ego View". A relatively small amount of training image data was needed to re-train a portion of the weights of the DNN. The DNN model was therefore used as the detection tool [31]. Classic Computer Vision methods of Optical Flow based image tracking were used to keep track of the feature points on the image for each vehicle [32]. LOESS method was used to smooth the displacement, velocity and acceleration.

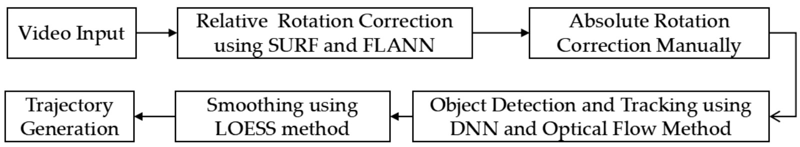


Figure 1. Trajectory generation workflow.

Similar to HighD data, lane numbers were set as 1–9, while lanes 1–4 represent lanes of upper road from driving from right to left and lane 6–9 are lower road from left to right. Lane one and nine represent the emergency lane, two and eight represent the slow lane, three and seven represent the middle. Lane four and six represent the fast lane and five represents the isolation belt. Cars and trucks were collected. Only car following and lane changing were observed in UAV view, and four vehicle following types were classified, including car following car(C-C), car following truck(C-T), truck following car(T-C), and truck following truck(T-T). Furthermore, vehicles in the emergency lane were extracted although not analyzed in this study.

Microscopic parameters, including velocity, acceleration, the offset between the vehicle and the lane center, minimum TTC and THW during car following and lane changing were subjected to the Kolmogorov–Smirnov test to evaluate the presence of a normal distribution. If normally distributed, they were subjected to a one-way analysis of variance for driving lane and vehicle following types. If not, a non-parametric Kruskal–Wallis test was performed. Vehicle types were set as an independent variable to investigate its influence. Post hoc pairwise comparisons using Tukey's honestly significant difference method were performed if there were significant differences. An alpha level of 0.05 was used. The mean and standard deviation were calculated for all parameters. Only TTC less than 100 were studied.

3. Results

3.1. Data Comparison

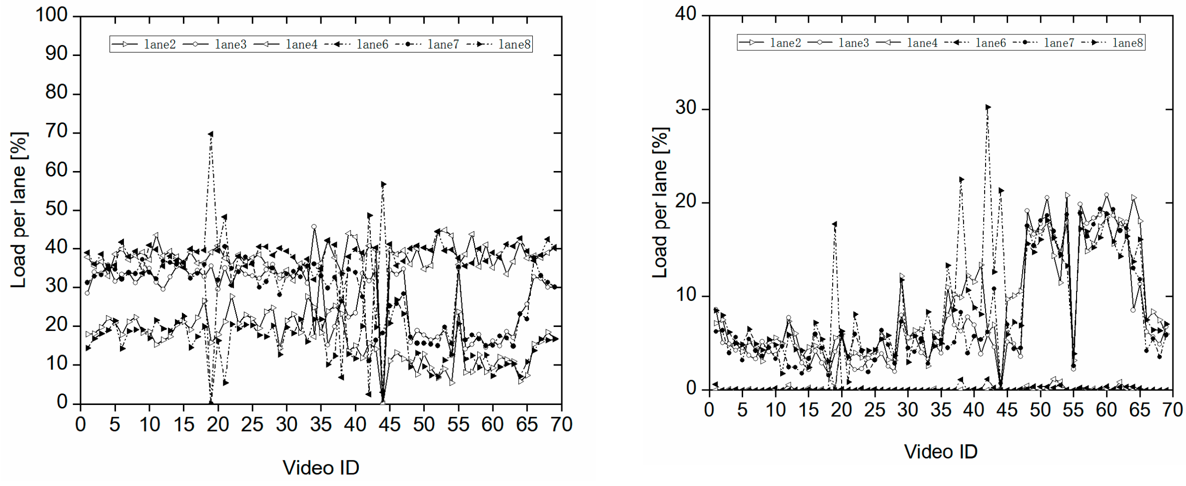
Data comparison between China and Germany was shown in Table 1. The data collected in this study were at the same level compared with HighD, although the amount of vehicles were less as a result of the lower velocity due to strict speed regulation and lower traffic density.

Table 1. Data comparison between China and Germany.

	Recording Duration [h]	**Lane (Per Direction)**	**Recorded Distance**	**Vehicles**	**Car**	**Truck**	**Driven Distance [km]**	**Driven Time [h]**
Ours	17.2	3 + 1	400–420	91,910	80,890	11,020	37,805	443
HighD	16.5	2 to 3	400–420	110,000	90,000	20,000	45,000	447

3.2. Macroscopic Results

Macroscopic results focused on the traffic flow rate, density and their relationships. Lane difference was also investigated. The parameter definitions were taken from a former study [15]. Figure 2 showed the traffic load in different lanes of cars and trucks and Figure 3 showed the ratio of trucks to cars in different lanes. The mix ratio of cars and trucks increased from the fast lane to slow lane, indicating a higher potential risk considering the blind zone and the traffic complexity. The relation between flow rate and load per lane were shown in Figure 4. The relation between flow rate and density were shown in Figure 5, and the influence of lanes was in Figure 6. The relation of lane changing times and flow rate and density between different vehicle types and lanes were shown in Figures 7 and 8.



(**a**) (**b**)

Figure 2. (**a**) Car load per lane of each lane in different videos; (**b**) Truck load per lane of each lane in different videos.

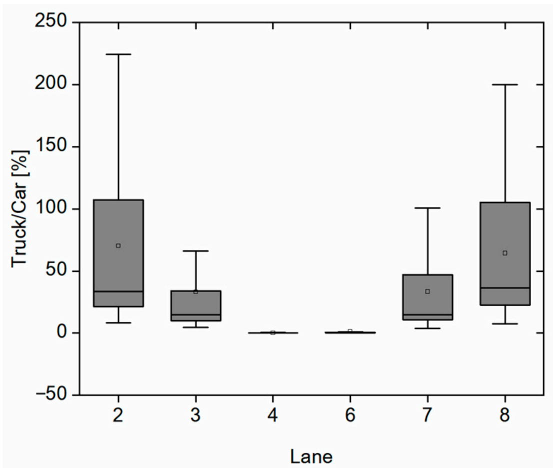
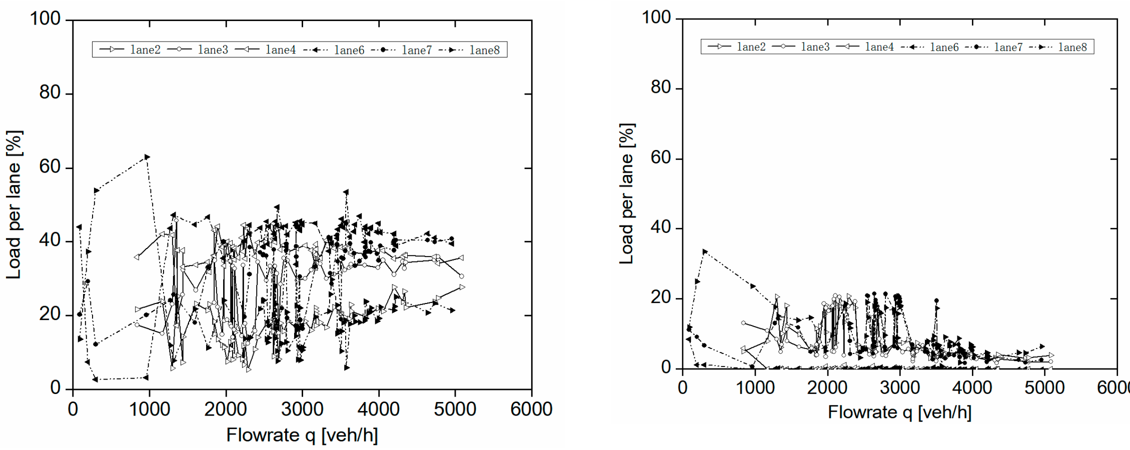
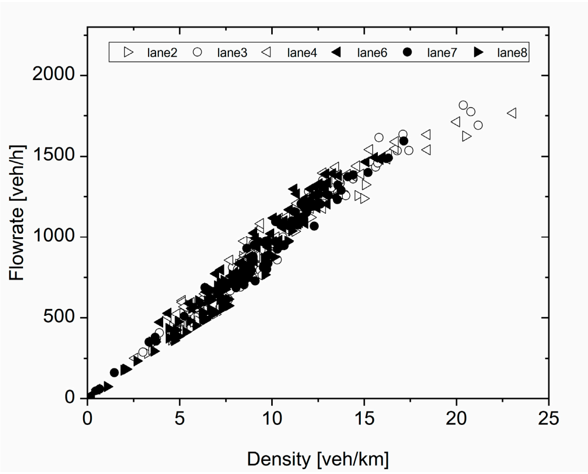


Figure 3. Relative proportion of truck and car in different lanes.

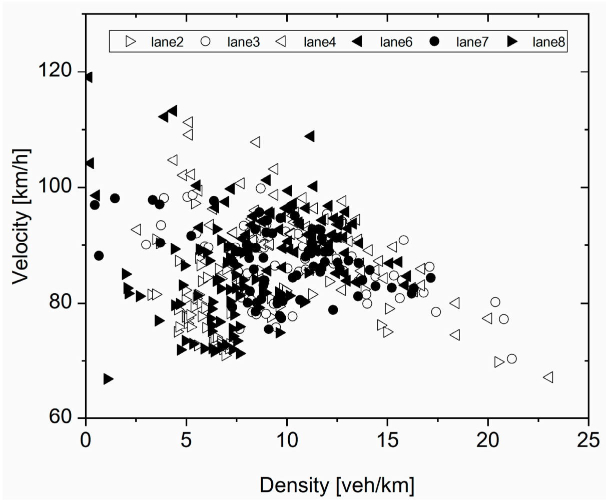


(**a**) (**b**)

Figure 4. (**a**) Car load per lane versus flow rate; (**b**) Truck load per lane versus flow rate.



(**a**)



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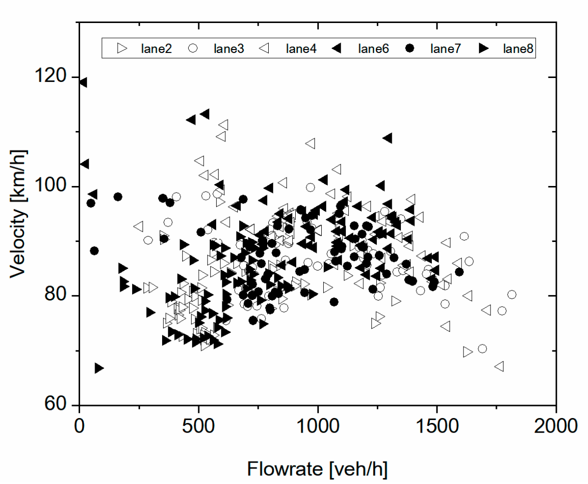


(**c**)

Figure 5. (**a**) Flow rate versus density; (**b**) Flow rate versus velocity; (**c**) Velocity versus density.

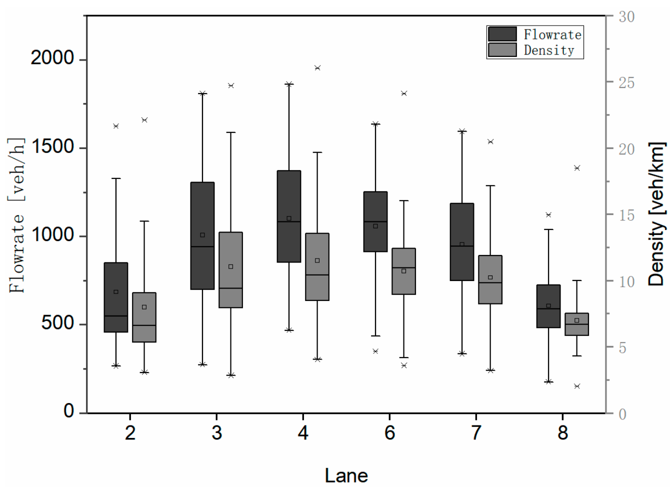
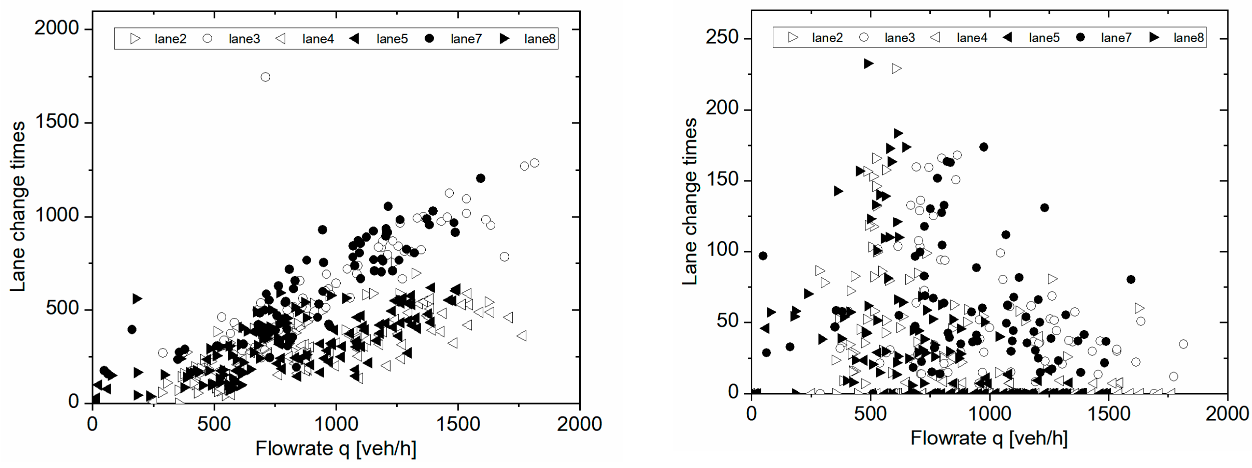
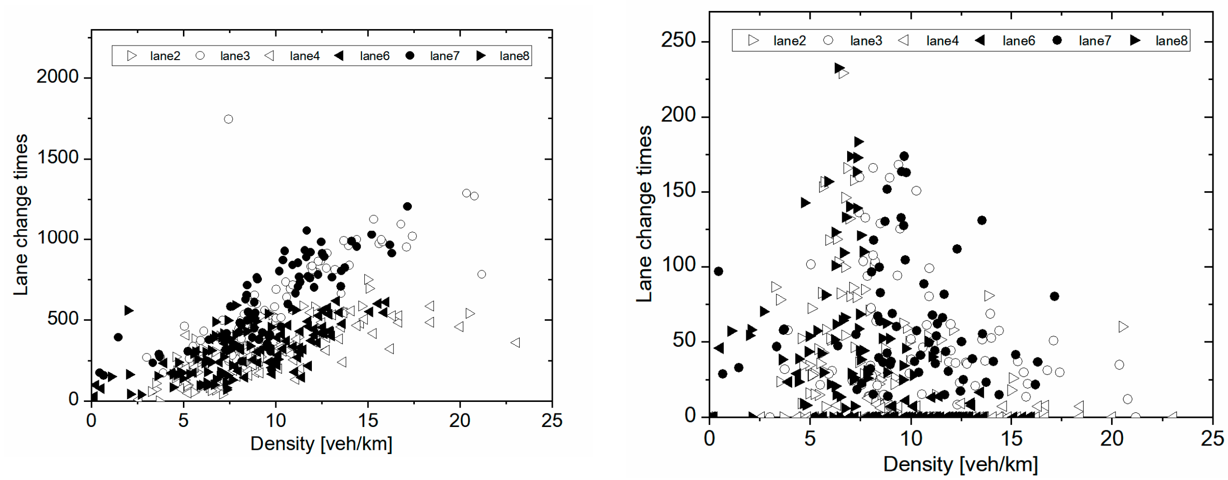


Figure 6. Flow rate and density in different lanes.



(**a**) (**b**)

Figure 7. (**a**) Car lane change times versus flow rate; (**b**) Truck lane change times versus flow rate.

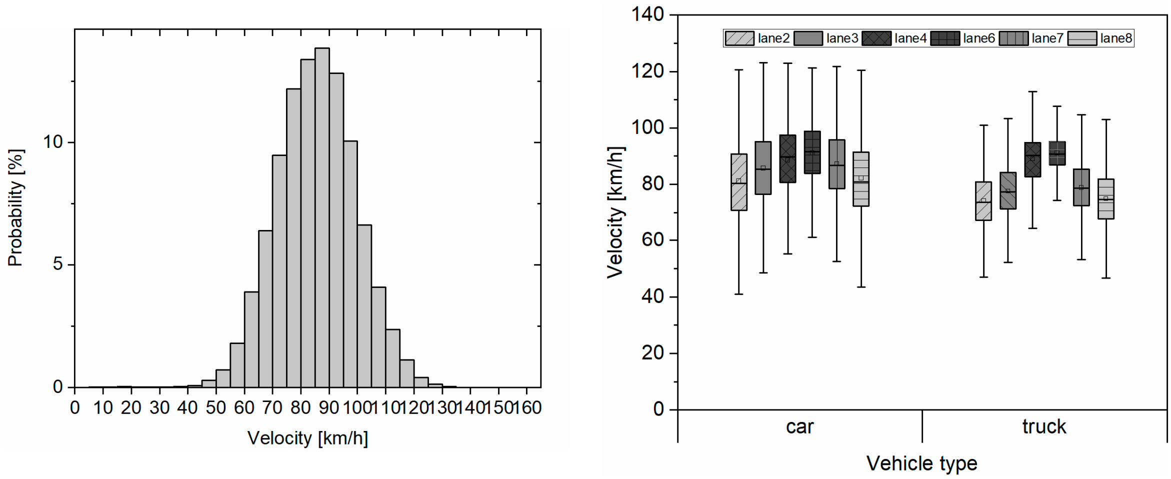


(**a**) (**b**)

Figure 8. (**a**) Car lane change times versus density; (**b**); Truck lane change times versus density.

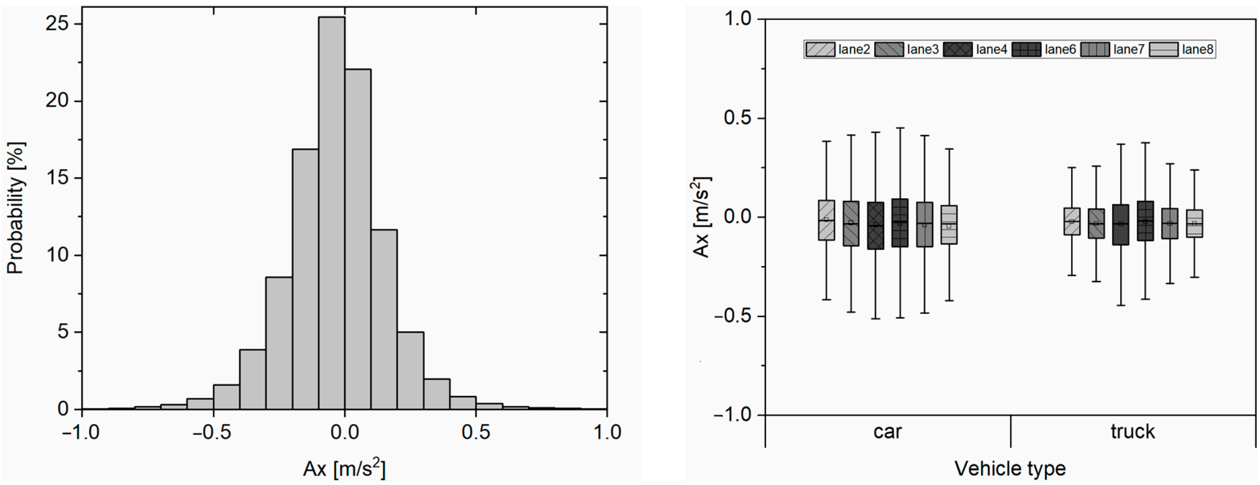
3.3. Microscopic Results

Microscopic results focused on velocity, acceleration, offset, TTCmin and THWmin. Probability distribution of velocity in the data and the differences of lane and vehicle types are shown in Figure 9. Probability distribution of longitudinal and lateral acceleration and the differences of lane and vehicle types are shown in Figure 10. Probability distribution of offset, in which a negative indicates left offset and positive indicates right, and the differences of lane and vehicle types, are shown in Figure 11. Probability distribution of TTCmin when car following and lane changing and the differences of lanes and following types are shown in Figure 12. THWmin Distribution and differences are shown in Figure 13. The mean and standard deviation were shown in Appendix A and a significant difference in parameters was shown.

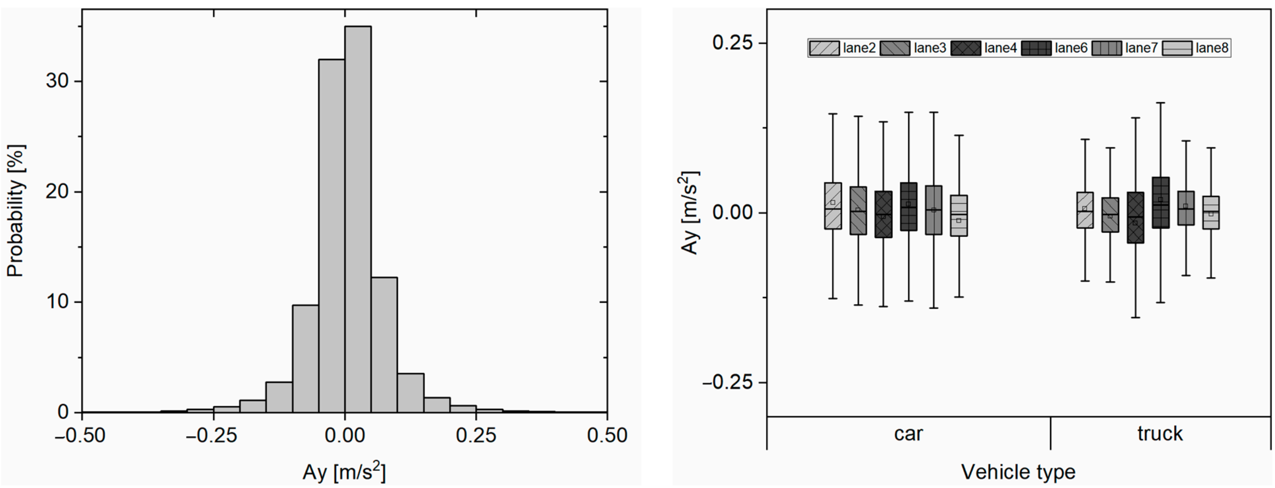


(**a**) (**b**)

Figure 9. (**a**) Probability distribution of velocity; (**b**) Velocity for car and truck in different lanes.



(**a**) (**b**)



(**c**) (**d**)

Figure 10. Probability distribution of longitudinal (**a**) and lateral (**b**) acceleration; Longitudinal (**c**) and lateral (**d**) acceleration for car and truck in different lanes.

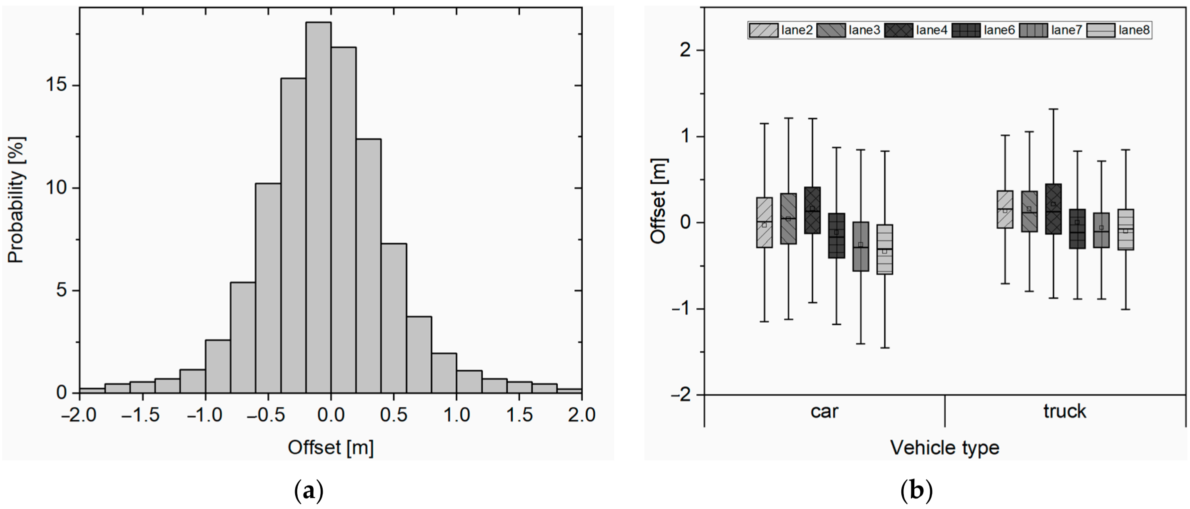


Figure 11. (**a**) Probability distribution of offset; (**b**) Offset for car and truck in different lanes.

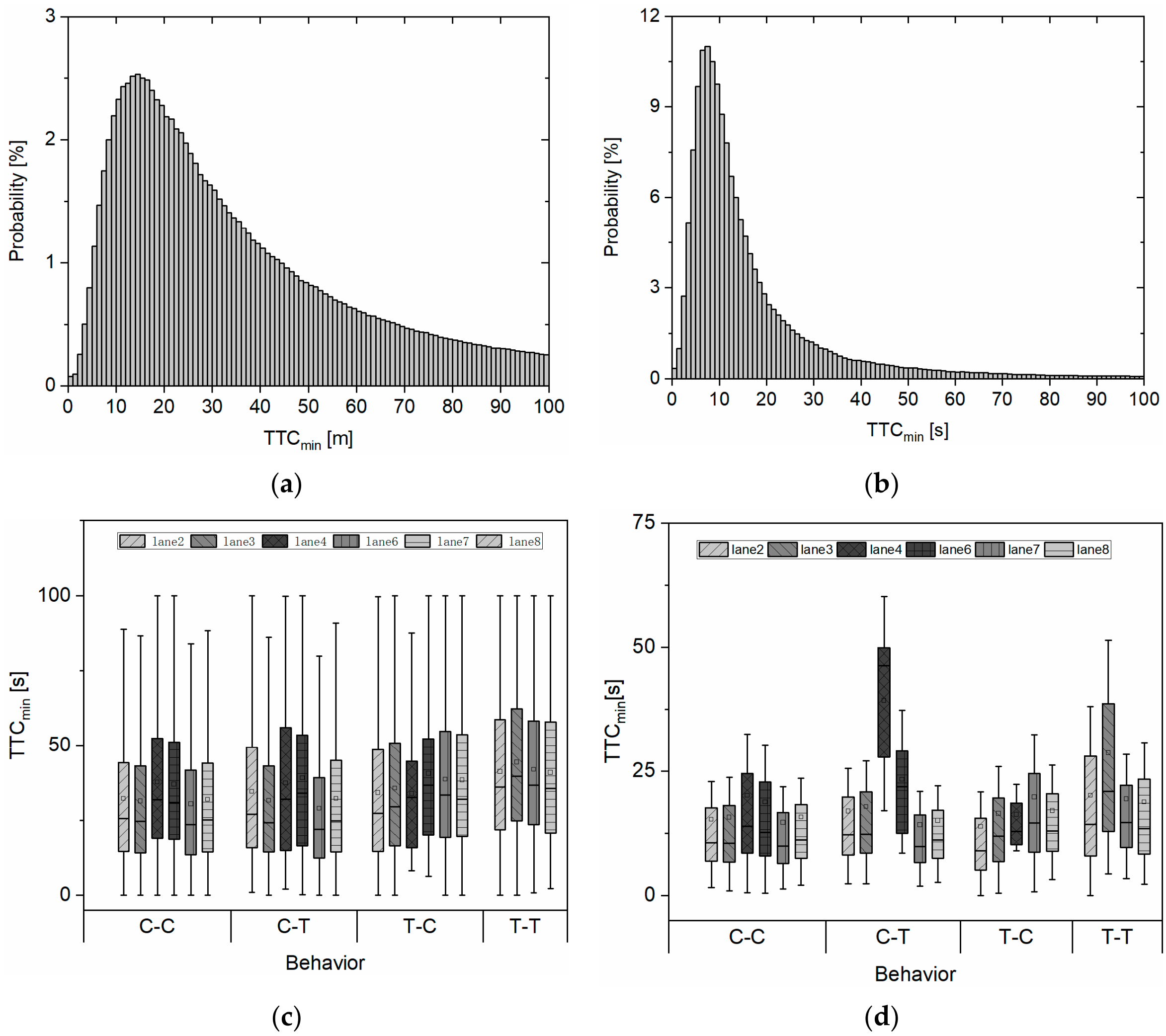


Figure 12. Probability distribution of TTCmin when car following (**a**) and lane changing (**b**); TTCmin when car following (**c**) and lane changing (**d**) for different following behavior in different lanes.

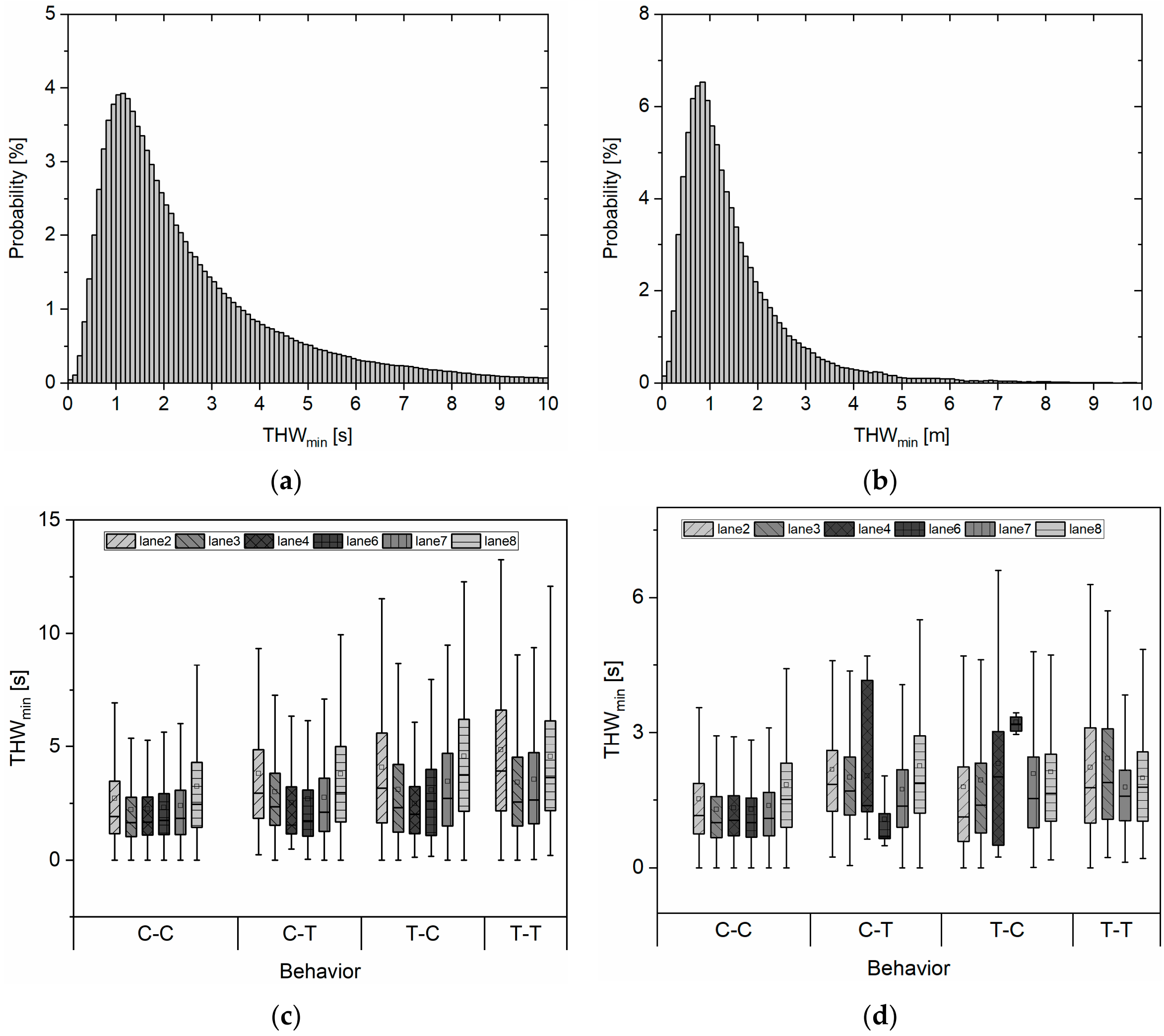


Figure 13. Probability distribution of THWmin when car following (**a**) and lane changing (**b**); THWmin when car following (**c**) and lane changing (**d**) for different following behavior in different lanes.

4. Discussion

4.1. Macroscopic Analysis

Higher load were found in the fast and middle lanes and it was different from the trends found in Germany [15], where the fast lane had a lower load. Cars were generally driving in the fast and middle lane and trucks in the slow lane. This was coincident with the regulation, in which it is suggested cars should drive in the left two lanes and trucks drive in the right two lanes. However, illegal usage of the fast lane was found for some trucks, and this will increase the complexity of the traffic.

The upper and lower road showed similar driving trends, except for in small flow rate conditions when less than 1000. With the increase in flow rate, the load in the fast lane remained unchanged, while the middle and slow lane increase slightly. This is different from Germany, where there was a significant decrease in the fast lane and increase in the slow lane. It can be assumed that drivers in China were more stable on highways. The trend in cars was similar, with the total one representing the large proportion. Lane load was jumping in [2000, 3000] although the amplitude was higher than the flow rate, which was larger than 3000 veh/h. Traffic density was in [0, 25], meaning that the traffic was in the 2nd level stable flow [33]. The influence of mix ratio was similar to other studies, in which velocity decreased and standard error increased with the truck portion [33]. Similar to HighD data, the flow rate was proportionate to the density, also indicating the traffic under free flow.

The change in velocity to flow rate was small, and only showed a small decrease when the flow rate is larger than 1500. Velocity in the fast lane decreased slightly and remained unchanged in the middle lane. It increased slightly in the slow lane when flow rate were in [400, 1000].

Velocity decreased with the growth in density, especially in the fast lane, while unchanged in the middle and slow lane. This was different from the significant decrease in HighD, and might result from the maximum velocity not being limited in Germany. Velocity is higher than 120 km/h when the density is small, which is illegal in China.

Significant differences were found in the flow rate and the density of different lanes. Both of them were larger in the fast and middle lane. This was related to the regulation requirement, which defines the driving region and speed limitation, where the speed in the slow lane is generally 20 km/h lower than the left two lanes.

Lane change time increased in all lanes with flow rate, while middle lane contributed the largest increment and fast lane contributed the smallest. Cars preferred to change lane in the fast lane when the flow rate was in [750, 1500] and in the slow lane when in [300, 750]. Trucks were mainly driving in the middle and slow lane and no significant difference was found for lane change time between them. Frequent lane change existed when the flow rate was in [500, 800]. Lane change time was less for trucks when the flow rate was close.

There is a similar relation between lane change time and density when the same lane was found. There were more lane change options for vehicles in the middle lane, which resulted in more lane change time, when the traffic load was the same. With the increase in flow rate and density, the lane change time for cars increased, yet decreased for trucks. This means trucks drove more conservatively than cars under the same traffic status.

4.2. Microscopic Analysis

Vehicles were commonly driving at 70 to 100 km/h, which is much slower than in Germany due to the speed limitation in China. In most highways, cars are limited to drive under 120 km/h and trucks should drives less than 100 km/h, although no limitation is set in Germany. This also accounts for the significant different in velocity of two vehicle types in our datasets. A larger difference value between the mean velocity and limitation was found for cars than trucks. Some cars drove faster than the limitation and the margin was higher than trucks, indicating that cars are more dangerous when performing aggressive behavior.

Trucks drove significantly faster in the fast lane, although no significant difference was found for cars in different lanes, with a slightly higher average velocity. Cars drove significantly faster than trucks in the middle and slow lane, although similar in the fast lane. It should be noticed that it is illegal for trucks to drive in the fast lane, which means a larger risk considering the larger weight and kinetic energy.

Longitudinal and lateral acceleration distribution were in the same level compared to the naturalistic driving dataset [3,34]. It also distributed in a similar way to the German data, although the Ax was biased to negative. It might result from the fact that Chinese drivers drove aggressively, yet have to decelerate more due to low approving speed in free flow, and the total traffic is more stable.

The longitudinal acceleration was significantly smaller in lane six and the lateral one was higher than other lanes, indicating that trucks contained more lateral risk when driving in the fast lane. Cars drove more stably since a significant difference was found for the acceleration of cars in both regions.

The offset of vehicle center to lane center mainly distributed in [-0.8, 0.8], and the average value is -0.03. It means that more pressure was put on the road on the left side despite most vehicles driving in the center region of the traffic lane.

A significant difference was found in vehicle types of the same lane, and cars tended to drive on the left side to the center and trucks drove in the right side. This might have resulted from the structure of the car and the driver view. For the car driver, it was difficult to acknowledge the behavior of the vehicle from the right side, with a lower vehicle body, longer distance to right rear-view monitor, and visual block of A pillar, so they adopted the left driving strategy. Trucks mainly drove in the left two lanes and they need to care about vehicles from left side, so they would drive in the middle or even with right side biased. An isolation belt existed in the left of the fast lane, so vehicles in the fast lane showed slight bias to the center and the right side. This might cause smaller lateral space between the fast and middle lane and increased the crash risk, with a higher velocity than other lanes.

TTCmin mainly distributed in [0, 20] when lane changing and car following, however, many cases larger than 20 were found for car following behavior, which is similar to the former study with the highest portion of the TTCmin region, near eight and ten [22]. TTCmin was significantly smaller when lane changing, which is coincident with the convention that lane changing was always a trigger in small TTC. A significant difference was found for various behaviors in different lanes when performing lane changing. For example, cars showed smaller TTC than trucks, and a smaller one existed in the middle lane. A similar behavior was found when car following, and significant small TTCmin existed in car-car following behavior in middle lane.

A significant large TTCmin was shown in the fast lane for car-car following behavior when lane changing, which might result from the larger following distance. Both cars and trucks adopted smaller TTC when lane changing if the front vehicle was a car. TTCmin of car-car following is smaller than truck-car when car following. It is more dangerous for cars when car following in the right two lanes, due to the significantly smaller TTCmin, than trucks.

THWmin mainly distributed in [0, 2] when lane changing, although many cases larger than two were found for car following behavior. This was similar to a former study in China, which found an average THW when car following was 2 s for a car and 3 s for a truck [21]. THWmin was significantly smaller when lane changing, which is also coincident with the convention. A significant difference was found for various following behaviors in different lanes when lane changing also.

Car-car following behavior showed the smallest THWmin and lane changing of cars was more dangerous than trucks in the middle lane. Car following of car-car behavior was more dangerous with the smaller THWmin, which might be related to the definition of THW. THW decreases with large velocity and the same distance, and the car-car pair is often faster than truck-truck pair. Cars showed more aggressive behavior, no matter whether it was cars or trucks in front, with smaller TTC and THW.

Shown in Table 2, differences exist in the distribution of THWmin and TTCmin in defined threshold, compared with HighD [marco]. THWmin was similar, yet the aggressive cases were more in China in a small boundary. The more obvious trend was found in TTCmin, as cases in which German drivers merely drove with TTCmin was less than two, yet more than 2000 cases were found in China.

Table 2. Frequency of THWmin and TTCmin in defined threshold.

THWmin<	Number	Frequency	TTCmin<	Number	Frequency
2	64,205	69.86%	8	20,386	22.18%
1	48,176	52.42%	4	7168	7.80%
0.6	15,027	16.35%	2	1949	2.12%
0.5	10,584	11.52%	1	675	0.73%
0.4	6572	7.15%	0.8	537	0.58%
0.25	2357	2.56%	0.4	357	0.39%
0.2	1457	1.59%	0.2	305	0.33%

5. Conclusions

This study investigated the typical Chinese driving behavior acquired from the UAV view. The results showed that there were large differences between China and Germany, and provide sufficient data for the development and localization of ICV. Different characteristics were found for different vehicle types, following behavior types and lanes, which is useful for making a proper decision strategy with regard to the ADAS and AD system. The design of road might be responsible for taking the driving offset, as cars tended to drive left and trucks tended to right, and this should be taken into account for improving the serviceable life of road.

Author Contributions: Conceptualization, C.L. and S.Z.; methodology, C.L., J.D., S.Z. and Y.X.; software, H.C. and Y.C.; validation, K.L.; formal analysis, C.L. and S.Z; investigation, C.L. and S.Z.; resources, S.Z. and K.L.; data curation, Y.X. and Y.C.; writing—original draft preparation, C.L. and S.Z.; writing—review and editing, J.D. and K.L.; visualization, C.L. and S.Z.; supervision, K.L. project administration, S.Z.; funding acquisition, S.Z. and K.L. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. The mean and standard deviation of velocity.

Lane	Car	SD	Truck	SD
2	81.19	15.10	74.18	10.33
3	85.73	14.17	77.59	9.74
4	88.56	13.88	89.01	8.48
6	91.09	12.14	91.10	9.03
7	87.36	13.07	78.86	9.58
8	82.24	14.68	74.88	10.62

Note: (1) No Significant between different lanes for car; (2) Significant difference between lane 4 to lane 2, 3, 6, 7, 8 and lane 6 to 2, 3, 4, 7, 8 for truck; (3) Significant difference between vehicle types in lane 2, 3, 4, 7, 8.

Table A2. The mean and standard deviation of longitudinal and lateral acceleration.

Lane	Car Ax	SD	Truck Ax	SD	Car Ay	SD	Truck Ay	SD
2	−0.013	0.19	−0.022	0.14	0.015	0.071	0.0060	0.050
3	−0.029	0.20	−0.032	0.13	0.0041	0.078	−0.0047	0.048
4	−0.039	0.20	−0.035	0.17	−0.0055	0.068	−0.015	0.074
6	−0.032	0.20	−0.021	0.17	0.013	0.070	0.019	0.067
7	−0.040	0.20	−0.033	0.14	0.0036	0.079	0.0098	0.049
8	−0.045	0.18	−0.033	0.13	−0.011	0.070	−0.0017	0.048

Note: (1) No Significant between different lanes for car; (2) Significant difference between lane 4 to lane 2, 3, 6, 7, 8 and lane 6 to 2, 3, 4, 7, 8 for truck; (3) Significant difference between vehicle types in lane 2, 3, 4, 7, 8.

Table A3. The mean and standard deviation of offset.

Lane	Car	SD	Truck	SD
2	−0.02924	0.51936	0.13609	0.42462
3	0.04506	0.54971	0.16066	0.40320
4	0.16321	0.44561	0.21475	0.51831
6	−0.11122	0.45846	0.00462	0.48857
7	−0.25454	0.55318	−0.05814	0.41285
8	−0.33220	0.49275	−0.09732	0.42071

Note: (1) No Significant between different lanes for car; (2) Significant difference between lane 4 to lane 2, 3, 6, 7, 8 and lane 6 to 2, 3, 4, 7, 8 for truck; (3) Significant difference between vehicle types in lane 2, 3, 4, 7, 8.

Table A4. The mean and standard deviation of TTCmin when car following.

Lane	Car-Car	SD	Car-Truck	SD	Truck-Car	SD	Truck-Truck	SD
2	32.21	22.63	34.56	23.58	34.23	24.76	41.29	24.56
3	31.40	22.55	31.58	22.41	35.72	24.28	44.39	24.13
4	37.72	23.50	37.49	25.14	33.91	20.39	-	-
6	37.06	23.29	39.23	26.17	40.67	24.48	-	-
7	30.46	22.33	28.96	21.95	38.75	23.64	42.02	23.48
8	31.97	22.53	32.21	22.97	38.43	23.80	40.99	24.43

Note: (1) No Significant between different lanes for car-car; (2) Significant difference between lane 4 to lane 2, 3, 6, 7, 8 and lane 6 to 2, 3, 4, 8 for car-truck; (3) Significant difference between lane 4 to lane 2, 3, 6, 7, 8 and lane 6 to 2, 4, 7, 8 for truck-car; (4) No Significance between different lanes for truck-truck; (5) Significant difference between type 1 and 4 in lane 2, 3, 7, 8, and type 2 and 4 in lane 3, 7, and type 1, 2 and 3 in lane 4, and type 1, 2 and 3 in lane 6.

Table A5. The mean and standard deviation of TTCmin when lane changing.

Lane	Car-Car	SD	Car-Truck	SD	Truck-Car	SD	Truck-Truck	SD
2	15.27	14.47	16.90	14.91	13.86	15.45	20.09	16.69
3	15.68	15.23	17.82	15.38	16.45	15.98	28.63	20.77
4	20.11	17.87	39.27	15.50	16.27	10.90	-	-
6	18.77	17.19	23.31	13.39	-	-	-	-
7	14.63	14.37	14.17	13.35	19.75	16.54	19.38	16.35
8	15.76	14.10	15.02	13.19	17.02	13.59	18.76	15.69

Note: (1) No Significant between different lanes for car-car; (2) Significant difference between lane 4 to lane 2, 3, 6, 7, 8 and lane 6 to 2, 3, 4, 7, 8 for car-truck; (3) Significant difference between all different lanes except lane 2 to 4 for for truck-car; (4) Significant difference between all different lanes for truck-truck; (5) Significant difference between all types in lane 2, 3, 7, 8, type 3 and 1, 2 in lane 4, and type 1 and 2, 3 in lane 6.

Table A6. The mean and standard deviation of THWmin when car following.

Lane	Car-Car	SD	Car-Truck	SD	Truck-Car	SD	Truck-Truck	SD
2	2.72	2.37	3.80	2.82	4.08	3.28	4.85	3.49
3	2.22	1.84	3.01	2.15	3.10	2.61	3.42	2.72
4	2.25	1.79	2.53	2.09	2.49	1.81	-	-
6	2.32	1.80	2.70	2.55	3.08	2.61	-	-
7	2.40	1.88	2.76	2.15	3.46	2.61	3.55	2.77
8	3.25	2.59	3.78	3.01	4.56	3.19	4.55	3.18

Note: (1) Significant difference between all other lanes between lane 2 and 4 and 8, and lane 6 to 7 for car-car; (2) Significant difference between all other lanes between lane 6 and 7 and 8, and lane 2 to 3 for car-truck; (3) Significant difference between all other lanes between lane 2 and 3 and 6, and lane 7 to 8 for truck-car; (4) Significant difference between all lanes for truck-truck; (5) Significant difference between type 1 and 4 in lane 2, 3, 7, 8, and type 2 and 4 in lane 3, 7, and type 1 and 2, 4 in lane4, and all types in lane 6.

Table A7. The mean and standard deviation of THWmin when lane changing.

Lane	Car-Car	SD	Car-Truck	SD	Truck-Car	SD	Truck-Truck	SD
2	1.52	1.20	2.17	1.36	1.78	1.86	2.22	1.58
3	1.29	1.06	2.00	1.32	1.94	1.82	2.42	2.24
4	1.32	1.05	2.03	1.43	2.30	2.08	-	-
6	1.29	1.06	1.07	0.93	3.23	0.79	-	-
7	1.37	1.06	1.73	1.30	2.08	1.86	1.78	1.30
8	1.83	1.36	2.25	1.49	2.12	1.83	1.98	1.32

Note: (1) Significant difference between all other lanes except lane 3 and 7, 8 for car-car; (2) Significant difference between all lanes for car-truck; (3) Significant difference between all other lanes except lane 4 and 3, 8 for truck-car; (4) Significant difference between all lanes except for truck-truck; (5) Significant difference between all types in lane 2, 3, 6, 7, 8 and type 3 and 1, 2 in lane 4.

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