How Far are Autonomous Vehicles from Driving in Real Traffic? The Adaptability Analysis of Autonomous Vehicles to Cut-in Scenarios in China

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How Far are Autonomous Vehicles from Driving in Real Traffic? The Adaptability Analysis of Autonomous Vehicles to Cut-in Scenarios in China

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Abstract At present, autonomous vehicle technologies (AVTs) have been extensively researched and developed, but there is less research focused on the adaptability of current AVTs to the real traffic. Whether AVTs can be competent in the real driving environment is still an issue. To fill the gap, this paper first collected a great amount of driving data from more than 60 Chinese drivers and established a big natural driving database covering millions of kilometers, all-weather and all working conditions. Then, using the dataset, 3044 cut-in scenarios related to automatic driving were extracted and their characteristics were analyzed based on the cluster method. According to the distribution of cut-in behavior, the related technical requirements of autonomous vehicles were clearly detailed, analyzed, and evaluated from the perspectives of perception, intelligent networking, and motion planning. Finally, from the comparative analysis, we draw the adaptation conclusions of the current AVTs to the real traffic and point out the unsolved challenges. Our conclusions could be very useful for motor corporations and researchers to draw their attention to the complexity of the Chinese traffic environment, and for policymakers to think about making new AVTs policies in anticipation of the advent of future autonomous vehicles.

Keywords Autonomous Vehicles · Adaptability · Cut-in Scenarios · Artificial Intelligence · China

1 Introduction

AVs are deemed as promising solutions for safer road transportation in the future (Chiou et al., 2020) and China is expected to become one of the largest markets for AVs.

With the advancement of AI and control technologies, in previous researches, the manuscripts paid attention to object detection (Wang et al., 2021), interaction (Rasouli and Tsotsos, 2019), receptivity (Deo and Trivedi, 2018; Geng et al., 2017), behavior prediction (Volz et al., 2018), motion estimation (Wang et al., 2021), etc. These researches are related to the adaptability but did not directly point out the adaptability. However, the adaptability of driverless technologies to real traffic is largely unknown and whether current AVTs can be competent in the real traffic is still a big question.
Similarly, review articles focused more on technologies as well, such as object detection (OD), motion estimation (ME), path planning (PP), etc. Generally, OD is reviewed to summarize and compare the detection algorithms according to the used sensors (Abduljabbar et al., 2019; Lai and Teoh, 2014). Additionally, Yang et al. summarized both the state of art and future perspectives of key technologies that are needed for future intelligent connected vehicles. Deb et al. summarized the factors that influence the AV’s behaviors, public acceptance of fully automated vehicles as well as current interacting interfaces between traffic participants (Deb et al., 2018). Siegel et al. summarized the state of the art in connected vehicles—from the need for vehicle data and applications thereof, to enabling technologies, challenges, and identified opportunities (Siegel et al., 2018). In these reviews, the detection methods, influencing factors and interacting interfaces were carefully summarized and these are closely related to adaptability. Nevertheless, there is a lack of systematic and direct analyses of the adaptability to pedestrians. Therefore, the adaptability analyses are valuable and need to be supplemented.

In this paper we have five contributions: 1) A natural driving database covering millions of kilometers, under all-weather scenarios and all working conditions of China was established;

2) Statistical characteristics of 3044 cut-in behaviors in Chinese highway scenarios, including environmental characteristics and driving behavior characteristics, were obtained based on cluster analysis;

3) The cutting-edge technologies related to the cut-in scenario of autonomous driving from the aspects of perception, intelligent networking, and motion planning were analyzed;

4) Combining the technical demands and technologies, we give out the adaptivity of driverless technologies to the cut-in scenario;

5) Based on the status of driverless technologies, we came up with some challenges and opportunities for autonomous vehicles in China.

The remainder of the paper is organized as follows. Section 2 explains the ideas and methods. Section 3 introduced the natural driving data, and analyzed the characteristics of Chinese driving behavior. In Section 4, according to the needs of Chinese highway cut-in scenarios, research on autonomous driving technology and analysis of the adaptability of the technology are carried out and based on this, the challenges and opportunities faced by future autonomous driving technology research are put forward. Section 5 is the conclusion.

2 Framework

The objective of this article is to figure out the adaptability of AVTs to real traffic by reviewing articles. The first question should be how to evaluate the adaptability logically. To analyze the adaptability step by step, we divided it into two main questions: what are the Chinese traffic’ characteristics and their technical demands for AVs, and what are the current abilities of AVTs when facing cut-in scenarios? By solving the first, we know the safety demands for Chinese environment, which would be worked as our criteria. Then, through reviewing articles, the current abilities of AVTs would be summarized. By combining the two answers, the adaptability would be analyzed and develop the answer to the adaptability of AVTs to Chinese real traffic. The methodology is shown in figure 1.

Fig. 1 Adaptability analysis framework of this paper

At first, a large amount of real driving data of Chinese drivers was collected, and multiple cut-in scenarios were extracted. Using cluster analysis method, we extracted the environmental characteristics and driving behavior characteristics of the cut-in scenarios.

Then, according to the demands, through academic search engines and authoritative websites, the AVTs was summarized and analyzed. In the process of inductive analysis, the terms "autonomous driving vehicle", "autonomous driving technology", "cut-in scenarios", "vehicle", "motion planning" and other terms are combined to sort out professional papers and screen out related research. One important thing is that our reviewed technologies are the newest researches and are hard to tell which autonomous level they belong to. Therefore,
we discuss the adaptability based on single technology rather than autonomous levels. Finally, the adaptability summary of every single technology would be our analyses of adaptability.

Finally, this paper answers the question of the adaptability of autonomous driving technology in Chinese highway cut-in scenarios. And in this process, some cutting-edge technical problems were discovered, which provided some research directions for the work of technicians in related fields.

3 Characteristics of cut-in scenarios in China

3.1 Natural driving data acquisition

3.1.1 Data acquisition equipment

The device of data acquisition supports online marking and offline playback. Among them, 3 cameras + Mobileye + millimeter wave radar + GPS were used to cover the vehicle body’s 274° field of view information, as shown in Figure 2. The data types obtained by the sensors are shown in Table 1 and the measurement accuracy is shown in Table 2.

![Fig. 2 Schematic diagram of installation of data acquisition equipment](image)

### Table 1 List of the main sensors of the collection equipment to collect signals

| Sensor type | Signal category | Signal variable |
|-------------|-----------------|----------------|
| Camera      | Target          | Target type    |
|             |                 | Target size    |
|             |                 | Target position|
|             |                 | Target speed   |
| Lane line   |                 | Lane line type |
|             |                 | Lane line equation|
| Radar       | Target          | Target type    |
|             |                 | Target size    |
|             |                 | Target position|
|             |                 | Target speed   |
| Mobileye    | Target          | Target type    |
|             |                 | Target size    |
|             |                 | Target position|
|             |                 | Target speed   |
| Traffic sign|                 | Sign type      |
|             |                 | Sign position  |
| Lane line   |                 | Lane line type |
|             |                 | Lane line equation|
| Warning message |           | HW           |
|             |                 | FCW           |
|             |                 | LDW           |

### Table 2 Accuracy list of main sensors of acquisition equipment

| Sensor type | Signal category | Precision          |
|-------------|-----------------|--------------------|
| Radar       | Target distance | ± 0.4m (Long focus mode), ± 0.1m (Short focus mode) |
|             | Horizontal angle accuracy | ± 0.1° (Long focus mode), ± 0.3°/60° | ± 1° @ 45° / ± 5° @ 60° (Short focus mode) |
|             | Speed accuracy   | ± 0.1km/h          |
| Mobileye    | Relative longitudinal distance | In 85% of cases, the error is less than max(10%, 2m) |
|             | Relative lateral longitudinal distance | Related to relative longitudinal distance |
|             | Target width     | In 90% of cases, the error is less than 10% |

3.1.2 Data acquisition results

A. Data acquisition scope

As of the end of 2020, this study has accumulated more than 1 million kilometers of road data collection. The collection area covers Northeast, North China, East China, West China, Central China, Southwest, South China and other regions. Natural driving data includes 43.3% of highway, 30.9% of urban roads, 23.6% of national highways and provincial highways, 2.2% of other roads. The natural driving data involves a variety of terrains and constitutes a diversified natural driving database.

B. Driver samples

The number of drivers participating in natural driving data collection exceeds 60, and the drivers are mainly male (96.61%). As shown in Figure 3, the ages of drivers are widely distributed between 20 - 55 years old. At the same time, the participating drivers take into account their different driving experience while ensuring the safety of driving outside.
3.2 Analysis of Characteristics of Cut-in scenarios

3.2.1 The clustering procedure

A. Selection of clustering parameters

**Analysis parameters:** entering the scenarios involves many descriptive variables. The static elements include weather, road shape, vehicle type, etc. The dynamic elements include the motion state of the adjacent vehicle and the ego vehicle, the relative motion, and so on. Since the single variable value of static elements (such as "sunny", "straight", and "small car") accounts for a relatively large amount, it is uneasy for the variable to become a prominent feature of the category. Comprehensive consideration to determine the variables used for cluster analysis include: ego vehicle speed, cut-in vehicle speed, cut-in vehicle longitudinal acceleration, time headway (THW) at the cut-in time.

**Evaluation parameters:** evaluation parameters are used to distinguish whether the cut-in scenarios are dangerous and then the clustering results are divided into two kinds of typical scenarios and dangerous scenarios. The variable selected for the longitudinal hazard degree is the Time to Collision minimum (TTCmin), and the variable selected for the lateral hazard degree is the lateral acceleration of the cut-in vehicle.

B. Clustering process

SPSS platform was used to conduct the hierarchical clustering process and determine the number of appropriate clustering categories. From the result in Figure 4, when the number of categories is 11, the downward trend of the line becomes very slow, so the number of categories can be set to 11.

Then, K-means clustering was used to cluster the cut-in scenarios with similar characteristics into one category. Assuming that the input sample is $S = \{x_1, x_2, \ldots, x_m\}$, the algorithm steps are:

1) Select the initial $k$ category centers, $u_1, u_2, \ldots, u_k$.

2) Update the center of each category to the mean of all samples belonging to that category.

$$
\mu_j = \frac{1}{|c_j|} \sum_{i \in c_j} x_i
$$

3) Repeat the next two steps until the category center change is less than a certain threshold. Generally, the number of iterations, the rate of cluster center change, and the least square error MSE are selected as the termination conditions. The clustering results are shown in Table 3.
### Table 3: the clustering result of the cut-in scenario

| NO. | Category                                | Frequency (%) | $V_{sv}$ (km/h) | $V_{mv}$ (km/h) | $A_{mxv}$ (m/s²) | THW (s) | $TTC_{min}$ average (s) | $TTC_{min}$ minimum (s) | $A_{myv}$ (m/s²) | $LRV$ (km/h) | Criticality |
|-----|-----------------------------------------|---------------|-----------------|-----------------|------------------|--------|--------------------------|----------------------|------------------|-------------|-------------|
| 1   | Cut in $SV$ mid-speed, $MV$ low-speed and dec. | 7.0           | 80              | 69              | -0.24            | 2.5    | 26.9                     | 1.2                  | 0.01             | -11         | C           |
| 2   | Cut in $SV$ high-speed, $MV$ high-speed with small THW | 14.9          | 95              | 115             | 0.06             | 0.8    | 126.5                    | 10.8                 | 0.01             | 20          | T           |
| 3   | Cut in $SV$ high-speed, $MV$ low-speed and dec. | 11.7          | 108             | 114             | 0.02             | 1.4    | 531.6                    | 4.3                  | 0.01             | 6           | T           |
| 4   | Cut in $SV$ high-speed, $MV$ low-speed and dec. | 9.6           | 101             | 88              | -0.03            | 2.8    | 111.7                    | 2.2                  | 0.00             | -13         | T           |
| 5   | Cut in $SV$ high-speed, $MV$ high-speed | 13.7          | 79              | 90              | 0.03             | 1.1    | 771.5                    | 4.3                  | 0.00             | 11          | T           |
| 6   | Cut in $SV$ high-speed, $MV$ acc. with small THW | 6.1           | 106             | 133             | 0.15             | 0.7    | 1731.3                   | 7.2                  | 0.01             | 27          | T           |
| 7   | Cut in $SV$ low-speed, $MV$ low-speed | 1.6           | 24              | 21              | 0.86             | 3.3    | 9.9                      | 1.3                  | 0.00             | 1           | C           |
| 8   | Cut in $SV$ mid-speed, $MV$ acc. | 7.2           | 63              | 80              | 0.10             | 1.0    | 78.3                     | 1.1                  | 0.00             | 17          | C           |
| 9   | Cut in $SV$ low-speed, $MV$ acc. | 4.1           | 39              | 54              | 0.39             | 1.4    | 2522.1                   | 1.4                  | 0.07             | 15          | C           |
| 10  | Cut in $SV$ high-speed, $Small THW$ | 16.5          | 86              | 103             | 0.05             | 0.9    | 296.6                    | 6.6                  | 0.00             | 18          | T           |
| 11  | Cut in $SV$ low-speed, $MV$ dec. | 7.7           | 57              | 61              | -0.16            | 1.6    | 246.4                    | 1.8                  | -0.02            | 4           | T           |

Note: $V_{sv}$—Subject vehicle velocity; $V_{mv}$—Merging vehicle velocity; $A_{mxv}$—Merging vehicle longitudinal acceleration; THW—time headway at the initial of cut in; $A_{myv}$—Merging vehicle lateral acceleration; $LRV$—longitudinal relative speed.

According to the minimum value of $TTC_{min}$ and the average value of $TTC_{min}$ in each category, category 1, category 7, and category 8 are judged to be dangerous scenarios. These three categories reflect the longitudinal risk during the cut-in process; according to the minimum and average values of $TTC_{min}$ in each category, category 9 is judged to be a dangerous scenario, which reflects the degree of lateral danger during the cut-in process; the remaining 7 categories with a higher frequency are typical scenarios. The clustering effect of the 11 types of cut-in scenarios are shown in Figure 5. The red color and different shapes of point groups identify 4 types of critical scenarios, and the other color and different shapes of point groups identify 7 types of typical scenarios.

#### 3.2.2 Characteristics of cut-in scenarios in China

The distribution of special areas in the 11 types of cut-in scenarios are shown in Table 4. Among the 4 types of dangerous scenarios, the most dangerous cut-in type working conditions in the area (marked in red in Table 4) account for the highest proportion of the 4 types of dangerous scenarios. The highest ratio is the most typical cut-in type working condition in this area (marked in green in Table 4).

The construction area is one of the more common special areas of highways in China. The most typical cut-in working condition is the fifth type scenario, and the most dangerous cut-in working condition is the first type scenario. The parameter distributions are shown in Figure 6.

The speed and acceleration distribution of the ego vehicle at the moment when the adjacent vehicle cuts in is shown in Figure 7a). It can be seen from the figure...
Table 4  the distribution of special areas in the cut-in scenario

| NO. | Category                                      | Bridge (%) | Tunnel (%) | CA (%) | TS (%) | Ramp (%) | ENT (%) | Exit (%) | ACC (%) | TJ (%) | LI (%) | LR (%) |
|-----|-----------------------------------------------|------------|------------|--------|--------|----------|---------|----------|---------|--------|--------|--------|
| 1   | Cut in SV mid-speed MV low-speed and dec.     | 8.66       | 3.77       | 20.39  | 0.00   | 9.52     | 22.22   | 0.00     | 0.00    | 0.35   | 0.50   | 0.00   |
| 2   | Cut in SV high-speed MV high-speed with small THW | 11.16    | 0.00       | 7.77   | 14.29  | 0.00     | 0.00    | 0.00     | 0.00    | 0.00   | 0.00   | 0.00   |
| 3   | Cut in SV high-speed MV acc.                 | 10.93      | 0.00       | 5.83   | 0.00   | 0.00     | 0.00    | 0.00     | 0.00    | 0.00   | 0.00   | 0.00   |
| 4   | Cut in SV high-speed MV low-speed and dec.   | 12.30      | 0.00       | 9.71   | 0.00   | 0.00     | 0.00    | 0.00     | 0.00    | 0.00   | 0.00   | 0.00   |
| 5   | Cut in SV high-speed MV high-speed           | 15.15      | 39.62      | 16.50  | 0.00   | 0.00     | 11.11   | 16.67    | 0.00    | 0.50   | 0.00   | 0.00   |
| 6   | Cut in SV high-speed MV acc. with small THW  | 5.35       | 1.89       | 0.00   | 0.00   | 0.00     | 0.00    | 0.00     | 0.05    | 0.00   | 0.00   | 0.00   |
| 7   | Cut in SV low-speed MV low-speed             | 0.46       | 0.00       | 2.91   | 0.00   | 9.52     | 0.00    | 33.33    | 1.00    | 0.25   | 0.00   | 0.50   |
| 8   | Cut in SV mid-speed MV acc.                  | 7.06       | 16.98      | 13.59  | 14.29  | 47.62    | 11.11   | 0.00     | 0.00    | 0.05   | 0.00   | 0.00   |
| 9   | Cut in SV low-speed MV acc.                  | 1.59       | 13.21      | 4.85   | 57.14  | 28.57    | 22.22   | 0.00     | 0.00    | 0.15   | 0.00   | 0.00   |
| 10  | Cut in SV high-speed Small THW               | 18.68      | 13.21      | 6.80   | 0.00   | 0.00     | 0.00    | 0.00     | 0.05    | 0.00   | 0.00   | 0.50   |
| 11  | Cut in SV low-speed MV acc.                  | 8.66       | 11.32      | 11.65  | 14.29  | 4.76     | 33.33   | 50.00    | 0.00    | 0.10   | 0.00   | 0.00   |

Note: CA—Construction area; TS—Toll station; ENT—Entrance; ACC—Accident; TJ—Traffic jam; LI—Lane increase; LR—Lane reduction.

Fig. 6 Velocity distribution of the most typical scenario in construction area

distributed in the higher speed range when it cuts in, reflecting that the target car chooses a higher speed than the following car to cut in when changing lanes to ensure safety; the acceleration value of the cut-in vehicle is mainly distributed in $-0.6 - 0.6m/s^2$, and the cut-in vehicle tends to use a uniform speed or a slight acceleration to complete the cut-in process.

The distance and THW distribution of the ego vehicle and the cut-in vehicle at the moment when the adjacent vehicle cuts in is shown in Figure 7c). The adjacent vehicle cuts in mainly within a range of 20m. Chinese drivers generally choose a shorter cut-in distance, which is potentially dangerous.

Figure 7d) shows the distribution of THW and TTC of the ego vehicle and the original following adjacent vehicle at the moment when the adjacent vehicle cuts in. It can be seen that when traveling on a high-speed or express road, the two workshops that are cut into the lane maintain a relatively high relative distance. According to the definition of Olsen (Olsen et al., 2020), it is basically a non-hazardous level.

3.3 Summary of cut-in scenarios characteristics

Based on the above analysis, the conclusions about the characteristics of Chinese cut-in scenarios are as follows: 1) The highway cut-in scenarios mostly contain
areas such as tunnels, traffic construction, traffic toll stations, slopes, highway entrances, and exits. 2) The speed of the ego vehicle is higher when the adjacent vehicle cuts in on a high-speed, and the acceleration value of the ego vehicle is mainly distributed in $0 - 0.2 \text{m/s}^2$. Tend to maintain a constant speed throughout the process. 3) When the adjacent vehicle cuts in, the speed are mostly distributed in the higher speed range and the acceleration value is mainly distributed in $0.6 - 0.6 \text{m/s}^2$. They tend to choose a higher speed than the vehicle behind when changing lanes, and use a constant speed or slight acceleration to complete the cut-in process to ensure safety. 4) Chinese drivers generally choose a shorter cut-in distance, and the adjacent vehicle mainly cuts in within 20 m, which is potentially dangerous. 5) In the highway cut-in scenarios, a relatively safe distance is maintained between the front and rear vehicles in the original lane.

4 Adaptability analysis of AVTs in the cut-in scenarios

4.1 Technical requirements for AVTs

As shown in Figure 8, based on the characteristics in section 3.3, we summarize what autonomous vehicles need to do when driving in the highway cut-in scenarios in China: 1) Perceive and confirm the cut-in scenarios beyond 20 m; 2) Recognize the adjacent vehicle at the rear side in time outside the range of 20 m; 3) Accurately and quickly judge the driving intention of the adjacent vehicle within 1.2s of identifying the vehicle at the rear side, and complete the prediction of its driving trajectory as much as possible; 4) Make appropriate driving decisions based on existing information.

4.2 The state-of-the-art analysis of AVTs

4.2.1 Cut-in scenarios recognition technologies

Besides the common overtaking scenarios, cut-in behavior is always prone to happen in some special locations, such as road entrances and exits, traffic accident areas, road construction areas, highway tunnels, toll stations, ramps, construction areas. To recognized the above locations, some AI-based methods are often used, including road structure detection, traffic signs

Fig. 7 Schematic diagram of installation information of naturalistic driving databases collection equipment

Fig. 8 Chinese typical cut-in scenarios
recognition, and V2I (Vehicle to Infrastructure communication) technologies.

A. Judgment from road structure

Recently, the recognition of road marked lanes has achieved good results. For example, as shown in Table 5 from KITTI, the recognition of road-marked lanes are fast and effective with an accurate rate of more than 95%.

However, there has been less research on cut-in-related location recognition. Kumar (Kumar et al., 2018) proposed a stacked deep network integration architecture that combines the latest CNN, bidirectional LSTM, and siamese style distance function learning for intersection recognition tasks. However, due to the small difference in geometric features of roads, the best F1-score obtained in the real data set is 82.4%. When the recognition distance is limited to 20m (section 4.1.a), F1-score dropped to 51.5%.

In general, the current level of research on road marked line recognition is high, but most studies only use road marked line recognition to delineate the drivable area. For the identification of cut-in-related location, outside the set range (20m), neither the camera nor the LiDAR can effectively determine the special area in front of the vehicle.

B. Traffic signs recognition

Traffic signs can anticipate possible cut-in behaviors in advance. However, the recognition of traffic signs related to the cut-in scenarios can only be estimated from the overall level. Judging from the research statistics of the top 6 algorithms on the German traffic sign data set (GTSRB) (Table 6), the accuracy of the recognition rate exceeds 99%, which can basically meet needs.

C. Obtaining through V2I technology

Affected by environmental conditions such as weather and light, autonomous environment perception systems have limitations and cannot accurately perceive all road conditions. For fixed special areas such as tunnels, toll stations, entrances and exits, it is more advantageous to use V2I to convey the information of the road ahead to the autonomous vehicle.

Existing researches have made great advancements in V2I technologies (Davis, 2012), such as collision avoidance (safe distance), road sign notification (curve speed warning), event management (emergency vehicle warning), etc.. However, due to the huge size of the network, in addition to the renewal of equipment, the communication between the vehicle and the equipment must also be realized, which requires a large investment of facility funds making requirements hard to be met at present.

For now, V2I technology cannot be implemented due to the difficulty of hardware equipment construction and insufficient software equipment security. The method of using V2I technology to identify special cut-in-related locations is unrealistic.

4.2.2 Adjacent Vehicle recognition technologies

Until now, the researchers paid more attention to forwarding vehicle recognition, yet the cut-in-related adjacent vehicles detection was somehow neglected. The most important thing for automatic driving in cut-in scenarios is to determine the location and intent of the adjacent vehicles.

A. Adjacent vehicle detection

From the top 10 research statistics of 3D Object Detection in Table 7 (performances of 10 top detectors of KITTI), we found that there is still big room for improvement in the accuracy of vehicle recognition rate. More serious is that these methods still can’t be used to detect the cut-in-related adjacent vehicles. Since that, the direction of movement of the rear side vehicle and the preceding vehicles are inconsistent, and the appearance characteristics of the lights and license plates of the two vehicles are different, as shown in Figure 9.

Specially, there are a few researches on the recognition of the rear side vehicles: Tseng(Tseng et al., 2014) used the video collected by the camera installed under the rearview mirror of the ego car to detect and obtained a detection rate of 96%, and even in a tunnel environment, it can still maintain a detection rate of 95.53%; Chang(Chang and Cho, 2008) and Dooley(Dooley et al. (2015) used the wheel characteristics of the rear side vehicle to identify the vehicle in a short distance, and the accuracy was maintained around 90%; in the simulation experiment, Ge(Ruhai et al., 2017) can effectively identify the rear side vehicle within a range of 60m, the recognition rate is 95%, and the single-frame image processing time is 25ms.

Overall, due to the lack of suitable real data sets, most studies can only conduct tests and simulation with
Table 5 performances of 10 top detectors of KITTI (data is summarized in Jan., 18, 2021)

| Rank | Method                      | MaxF  | AP    | PRE   | REC   | FPR   | FNR   | Runtime |
|------|-----------------------------|-------|-------|-------|-------|-------|-------|---------|
| 1    | Pseudo-LiDAR                | 98.05%| 95.63%| 97.89%| 98.21%| 2.33% | 1.79% | n       |
| 2    | PLARD (Chen et al., 2019)   | 97.77%| 95.64%| 97.75%| 97.79%| 2.48% | 2.21% | 0.16s   |
| 3    | DFM-RTFNet                  | 97.59%| 95.60%| 97.59%| 97.59%| 2.65% | 2.41% | 0.03 s  |
| 4    | ZongNet                     | 97.53%| 93.05%| 97.12%| 97.94%| 3.19% | 2.06% | 0.16s   |
| 5    | SNE-RoadSeg (Fan et al., 2020) | 97.47%| 95.63%| 97.32%| 97.61%| 2.96% | 2.39% | 0.2s    |
| 6    | FDS-DeepLabv3+              | 97.45%| 95.63%| 97.33%| 97.58%| 2.94% | 2.42% | 0.05 s  |
| 7    | RBANet (Sun et al., 2019)   | 97.38%| 92.67%| 96.70%| 98.08%| 3.68% | 1.92% | 0.16s   |
| 8    | CLCFNet                     | 97.24%| 93.84%| 97.99%| 96.51%| 2.18% | 3.49% | 0.02s   |
| 9    | LC-CRF (Gu et al., 2019)    | 97.22%| 94.91%| 96.93%| 97.52%| 3.40% | 2.48% | 0.03s   |
| 10   | LidCamNet (Caltagirone et al., 2019) | 96.88%| 95.51%| 97.28%| 96.88%| 2.98% | 3.12% | 0.15s   |

Table 6 recognition-rate accuracy of various methods on GTSRB

| Paper                          | Method                        | Accuracy(%) |
|--------------------------------|-------------------------------|-------------|
| Alvaro et al. (Arcos-Garcia et al., 2018) | Single CNN with 3 STNs | 99.71       |
| Jin et al. (Jin et al., 2015) | HLSGD (20 CNNs ensemble)      | 99.65       |
| Ciregan et al. (Ciregan et al., 2012) | MCDNN (25 CNNs committee)    | 99.46       |
| Yu et al. (Yu et al., 2016)   | GDBM                          | 99.34       |
| Stallkamp et al. (Stallkamp et al., 2011) | Human performance (best) | 99.22       |
| Juristic et al. (Jurisić et al., 2015) | OneCNN                      | 99.11±0.10  |

Table 7 performances of 10 top detectors of KITTI (data is summarized in Jan., 18, 2020)

| Rank | Method                      | Easy  | Moderate | Hard  | Runtime |
|------|-----------------------------|-------|----------|-------|---------|
| 1    | HIKVISON-ADLAB-HZ           | 89.00%| 82.83%   | 76.00%| 0.1s    |
| 2    | SE-SSD                      | 91.49%| 82.54%   | 77.15%| 0.03s   |
| 3    | EA-M-RCNN (Border-Att)      | 87.77%| 82.33%   | 77.37%| 0.08s   |
| 4    | HUAWEI Octopus              | 88.26%| 82.13%   | 77.41%| 0.1s    |
| 5    | ADLAB                       | 90.92%| 82.08%   | 77.36%| 0.05s   |
| 6    | PV-RCNN-v2                  | 90.14%| 81.88%   | 77.15%| 0.06s   |
| 7    | RangeRCNN-LV                | 88.76%| 81.85%   | 77.18%| 0.1s    |
| 8    | PVGNet                      | 89.94%| 81.81%   | 77.09%| 0.05s   |
| 9    | PLNL-3DSSD                  | 88.98%| 81.69%   | 74.90%| 0.08 s  |
| 10   | DomainAdp                   | 88.64%| 81.66%   | 77.08%| 0.09s   |

self-collected data and cannot guarantee a high level of recognition accuracy at a long distance, thus cannot meet the technical requirements.

B. Adjacent vehicle intention recognition and trajectory prediction

In the occurrence and completion process of the cut-in scenarios, predicting the intention and trajectory of the adjacent vehicle is very important. It is not only the indicator for judging whether the cut-in scenarios will occur, but also has a vital influence on the subsequent decision-making and path planning.

In this area, most studies use NGSIM datasets based on a bird’s-eye view (Montanino and Punzo, 2013). Such studies usually use vehicle models to predict the trajectory of the vehicle in the next period of time (Guan et al., 2019; Zhao et al., 2020); or use classification and regression algorithms (Chen et al., 2020; Deo and Trivedi, 2018; Zhu et al., 2019) to analyze a large amount of data to identify the driving intention and predict the future driving trajectory.

However, the researches based on a bird’s-eye perspective cannot be adapted to the autonomous vehicle itself, and the sensor does not have the ability to identify the location and past trajectories of all vehicles on the road. It cannot meet the needs of autonomous vehicles in cut-in scenarios.

C. V2V technologies

V2V (Vehicle-to-Vehicle communication) technology is a critical way to realize the intention recognition and trajectory prediction of autonomous vehicles under the omniscience and omnipotence perspective. Research by the US Department of Transportation also shows (Juliussen, 2012) that up to 82% of automobile accidents can be avoided by the V2V system.

But like V2I technology, on the one hand, the installation and application of supporting equipment require a lot of manpower and financial resources; on the other hand, vehicle-to-vehicle Communication is not secure when DSRC (Dedicated Short Range Communication) technology has certain technical defects and
C-V2X (Cellular Vehicle-to-Everything) deployment is not yet complete, and it is easy for criminals to steal the daily driving track, hobbies and other data of the vehicle (Dibaei et al., 2019; Sarker et al., 2019). The application of this technology cannot meet the actual needs of autonomous vehicles, and it is also not the focus of our current research.

4.2.3 Vehicle motion planning

The motion planning module includes two parts: action planning and path planning. The action planning is mainly used to plan short-term or even instantaneous actions, such as turning, obstacle avoidance, overtaking and other actions, which is suitable for the needs of cut-in scenarios.

Recently, most of the works plan the vehicle’s path by using the Voronoi diagram (an occupancy grid algorithm) or driving corridors algorithm, but these types of traditional methods require full interaction with other moving objects around to improve the safety (Kattrakazas et al., 2015). In addition, autonomous vehicles can also learn the driver’s behavior based on driving data (Zhang et al., 2018; Zhao et al., 2020), but such methods require huge computing power and only show good performance when executed on a cloud computing architecture with strong computing power and heat dissipation capabilities. At present, this technology is relatively mature and can meet application requirements for cut-in scenarios.

4.2.4 Summary

Based on the above analysis, Table 8 summarizes the adaptability of AVTs to Chinese cut-in scenarios with the evaluation standard of fully meet and unmet.

First, until now, the recognition technologies can well detect road marked lines, traffic signs and ordinary vehicles in cut-in scenarios, but there still has the room for improvement in the detection of intersection, and the recognition of vehicle driving intention is poor.

Second, the trajectory prediction research of adjacent vehicle is unsuitable for autonomous vehicles. Intelligent networking technologies can transmit information between autonomous vehicles and transportation facilities and other vehicles, but it requires a complete transportation infrastructure and a certain vehicle networking communication standard.

In addition, there are fewer relevant data sets about the perspective of the rear side vehicles. Therefore, current AVTs cannot fully match the technical requirements, and cannot adapt to the cut-in scenarios of Chinese.

4.3 Challenges & opportunities

Overall, until now, AVTs has made great efforts but it still face many problems when entering real traffic such as the cut-in scenarios in China. Therefore, we summarized some cutting-edge technical issues which are challenging but unresolved.

A. Recognition of the cut-in scenarios

In addition to the construction of transportation infrastructure and the upgrade of equipment (sensors, CPU), The recognition of special areas related to the cut-in scenarios can help autonomous vehicles to make intention judgments and trajectory predictions for surrounding vehicles. However, the current research has not done in-depth research on the classification and recognition of traffic scenarios such as entry and car following. Extensive research should be carried out in this field.

B. Recognition of the rear side vehicles

The rear side vehicles are the common types of vehicles in cut-in scenarios. However, the current researches do not have an in-depth study on the recognition of the rear side vehicles, and the data set related to the rear side vehicles is also insufficient. More efforts should be made to improve its recognition performance.

C. Prediction of vehicle intention and trajectory

Intention recognition of nearby vehicles and prediction of future trajectories are critical to the autonomous vehicles in the cut-in scenarios. However, most current algorithms are based on the bird’s-eye perspective, and efforts should be made to transplant these algorithms into the ego vehicle perspective.

D. Establishment of cut-in-related dataset

The currently widely used data set is the front view angle of a vehicle-mounted camera or the bird’s-eye view angle of a fixed camera, which does not fully meet the needs of cut-in scenarios. It is recommended to collect driving data based on the rear side cameras to form a data set for subsequent research.

5 Conclusion

The purpose of this paper is to analyze the adaptability of current AVTs in Chinese cut-in scenarios. We first obtained Chinese natural driving data with the help of more than 60 Chinese drivers and extracted 3044 cases of cut-in scenarios from it. Secondly, using the key data (speed, acceleration, THW, TTC, etc.) of the drivers in the process of following, changing lanes, and overtaking to analyze the environmental characteristics and driving behavior characteristics of the Chinese cut-in scenarios. Thirdly, based on the obtained characteristics, we summarized the technical requirements in terms of
Table 8 Adaptability of autonomous vehicles to Chinese highway cut-in scenarios

| Technical demands                  | Evaluation | Limitations and suggestions                                      |
|-----------------------------------|------------|------------------------------------------------------------------|
| Traffic road recognition          | Fully meet |                                                                  |
| Recognition & prediction technology|            |                                                                  |
| Intersection recognition          | Unmet      | Recognition accuracy and distance is not enough (The highest F1-score within 15m is 88.2%) |
| Traffic signs recognition         | Fully meet |                                                                  |
| Object recognition                | Fully meet |                                                                  |
| Intent and trajectory prediction  | Unmet      | The research is based on a bird’s eye view and does not meet the needs. |
| V2X technology                    | V2I&V2V    | The hardware device does not meet the requirements.               |
| Autocontrol technology            | Motion planning | Fully meet |
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Sun JY, Kim SW, Lee SW, Kim YW, Ko SJ (2019) Reverse and boundary attention network for road segmentation. In: Proceedings of the IEEE International Conference on Computer Vision Workshops, pp 0–0

Gu S, Zhang Y, Tang J, Yang J, Kong H (2019) Road detection through crf based lidar-camera fusion. In: 2019 International Conference on Robotics and Automation (ICRA), IEEE, pp 3832–3838

Caltagirone L, Bellone M, Svensson L, Wahde M (2019) Lidar–camera fusion for road detection using fully convolutional neural networks. Robotics and Autonomous Systems 111:125–131

Kumar A, Gupta G, Sharma A, Krishna KM (2018) Towards view-invariant intersection recognition from videos using deep network ensembles. In: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, pp 1053–1060

Arcos-Garcia A, Alvarez-Garcia JA, Soria-Morillo LM (2018) Deep neural network for traffic sign recognition systems: An analysis of spatial transformers and stochastic optimisation methods. Neural Networks 99:158–165

Jin J, Fu K, Zhang C (2015) Traffic sign recognition with hinge loss trained convolutional neural networks. IEEE Transactions on Intelligent Transportation Systems 15(5):1991–2000

Ciregan D, Meier U, Schmidhuber J (2012) Multicolumn deep neural networks for image classification. In: 2012 IEEE conference on computer vision and pattern recognition, IEEE, pp 3642–3649

Yu Y, Li J, Wen C, Guan H, Luo H, Wang C (2016) Bag-of-visual-phrases and hierarchical deep models for traffic sign detection and recognition in mobile laser scanning data. ISPRS Journal of Photogrammetry and Remote Sensing 130:107–123

Stallkamp J, Schlipsing M, Salmen J, Igel C (2011) The german traffic sign recognition benchmark: a multi-class classification competition. In: The 2011 international joint conference on neural networks, IEEE, pp 1453–1460

Jurišić F, Filković I, Kalafatić Z (2015) Multiple-dataset traffic sign classification with oneccm. In: 2015 3rd IAPR Asian Conference on Pattern Recognition (ACPR), IEEE, pp 614–618

Davis G (2012) V2i safety applications: An overview of concepts and operational scenarios. New Jersey State Chapter of ITS America

Tseng DC, Hsu CT, Chen WS (2014) Blind-spot vehicle detection using motion and static features. International Journal of Machine Learning and Computing 4(6):516

Chang WC, Cho CW (2008) Real-time side vehicle tracking using parts-based boosting. In: 2008 IEEE International Conference on Systems, Man and Cybernetics, IEEE, pp 3370–3375

Dooley D, McGinley B, Hughes C, Kilman L, Jones E, Glavin M (2015) A blind-zone detection method using a rear-mounted fisheye camera with combination of vehicle detection methods. IEEE Transactions on Intelligent Transportation Systems 17(1):264–278

Ruhai G, Xuefeng Z, Meijuan Z (2017) Research on algorithms of identifying and tracking rear side vehicle based on prescan. Automobile Technology 8(8):32–37

Montanino M, Punzo V (2013) Making ngsim data usable for studies on traffic flow theory: Multistep method for vehicle trajectory reconstruction. Transportation Research Record 2390(1):99–111

Guan D, Zhao H, Zhao L, Zheng K (2019) Intelligent prediction of mobile vehicle trajectory based on space-time information. In: 2019 IEEE 89th Vehicular Technology Conference, IEEE, pp 1–5

Zhao Z, Fang H, Jin Z, Qin Q (2020) Gisnet: Graph-based information sharing network for vehicle trajectory prediction. arXiv preprint arXiv:200311973

Chen G, Hu L, Zhang Q, Ren Z, Gao X, Cheng J (2020) St-lstm: Spatio-temporal graph based long short-term memory network for vehicle trajectory prediction. In: 2020 IEEE International Conference on Image Processing (ICIP), IEEE, pp 608–612

Zhu J, Qin S, Wang W, Zhao D (2019) Probabilistic trajectory prediction for autonomous vehicles with attentive recurrent neural process. arXiv preprint arXiv:191008102

Juliussen E (2012) V2x technology’s arrival key to accident reduction and prevention. RJ iSupply Q 2:2012

Dibaei M, Zheng X, Jiang K, Maric S, Abbas R, Liu S, Zhang Y, Deng Y, Wen S, Zhang J (2019) An overview of attacks and defences on intelligent connected vehicles. arXiv preprint arXiv:190707455

Sarker A, Shen H, Rahman M, Chowdhury M, Dey K, Li F, Wang Y, Narman HS (2019) A review of sensing and communication, human factors, and controller aspects for information-aware connected and automated vehicles. IEEE Transactions on Intelligent Transportation Systems 21(1):7–29

Katrakazas C, Quddus M, Chen WH, Deka L (2015) Real-time motion planning methods for autonomous on-road driving: State-of-the-art and future research directions. Transportation Research Part C 60:416–442

Zhang S, Chen J, Lyu F, Cheng N, Shi W, Shen X (2018) Vehicular communication networks in the automated driving era. IEEE Communications Magazine 56(9):26–32