# Perspective, Survey and Trends: Public Driving Datasets and Toolsets for Autonomous Driving Virtual Test

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first serious fatal accident of an autonomous driving car [5]. Extensive research [3] [4] shows that autonomous driving faces more demanding safety and reliability requirements than traditional automotive.

# A. Challenges and Problems

With the rapid development of deep learning that covers end-to-end learning, owing to the merits of early safety and reliability guarantee, autonomous driving virtual testing has recently gains increasing attention compared with closed-loop testing in real scenarios [6] [7]. With the rapid development of big data-driven, extensive research shows the availability and quality of autonomous driving datasets and toolsets are the premise to diagnose the autonomous driving system bottlenecks and improve the system performance [8] [9] [10]. However, due to the diversity and privacy of the datasets and toolsets, collecting and featuring the perspective and quality of datasets and toolsets for virtual testing of autonomous driving become not only time-consuming but also increasingly challenging.

However, the recent research of autonomous driving datasets and toolsets in autonomous driving virtual testing faces two main challenges as follows:

- How to survey the recent increasing datasets and toolsets for autonomous driving virtual test using a systematic method? Recently there are some surveys, for example [11] and [12], show the urgent demands about the datasets and environments of autonomous driving test. However, they paid more attention to the results analysis and a formal systematic survey process for autonomous driving test still lacks.
- What are the recent findings and trends of both toolsets and datasets with scenario concerned so far? Although datasets and toolsets are the foundations of autonomous tests and there are some recent survey papers on datasets [13] [14], only [15] recently reviewed the virtual test platforms. However, [15] paid more attention on exploring the simulator of autonomous driving, but lacks tools

Abstract—Owing to the merits of early safety and reliability guarantee, autonomous driving virtual testing has recently gains increasing attention compared with closed-loop testing in real scenarios. Although the availability and quality of autonomous driving datasets and toolsets are the premise to diagnose the autonomous driving system bottlenecks and improve the system performance, due to the diversity and privacy of the datasets and toolsets, collecting and featuring the perspective and quality of them become not only time-consuming but also increasingly challenging. This paper first proposes a Systematic Literature review approach for Autonomous driving tests (SLA), then presents an overview of existing publicly available datasets and toolsets from 2000 to 2020. Quantitative findings with the scenarios concerned, perspectives and trend inferences and suggestions with 35 automated driving test tool sets and 70 test data sets are also presented. To the best of our knowledge, we are the first to perform such recent empirical survey on both the datasets and toolsets using a SLA based survey approach. Our multifaceted analyses and new findings not only reveal insights that we believe are useful for system designers, practitioners and users, but also can promote more researches on a systematic survey analysis in autonomous driving surveys on dataset and toolsets.

#### I. INTRODUCTION

Safety is the most critical requirement in autonomous driving test at the era when the automation level of autonomous driving cars reaches SAE3 or higher where the driving responsibility is gradually shifting from traditional drivers to autonomous driving cars [1] [2]. Recent safety research [1] [3] [4] shows that autonomous driving still faces huge challenges in complex interactive scenarios and unstructured environments, such as campuses with surging people and high-speed fog on highways. For example, Uber recorded the

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Duing to the page limitations, we have not released detailed information on the toolsets and datasets in this paper. For specific open source datasets and toolsets, please contact ruanli@buaa.edu.cn.

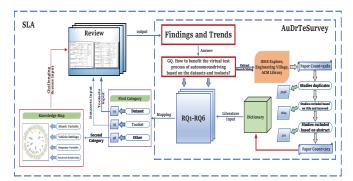


Fig. 1: Autonomous Driving Virtual Test Systematic Literature Review framework.

to establish other testing processes. Moreover, they are based on the papers before 2018 which lacks those of 2020.

#### B. Main Contributions

To solve these essential challenges in autonomous driving virtual test, we presents a survey of datasets and toolsets for autonomous driving virtual test from 2000 to 2020. The major contributions of this paper are summarized as follows:

- To the best of our knowledge, we are the first propose a Systematic Literature Review (SLR) approach for autonomous driving tests.
- We present a review of the datasets and toolsets for automated driving virtual tests based on the investigation research from 2000 to 2020. Quantitative findings with the scenarios concerned, perspectives and trend inferences and suggestions with the most important 35 automated driving test tool sets and 70 test data sets are also presented. To the best of our knowledge, we are the first to perform such recent empirical systematic survey on both the datasets and toolsets using a SLA based survey approach.

### C. Organization

The remainder of this paper is organized as follows: Section II introduces the SLA based autonomous driving research survey approach. SectionIII introduces results and trends inferences. The paper is concluded in SectionV.

# II. AUDRTESURVEY: SYSTEMATIC LITERATURE REVIEW APPROACH FOR AUTONOMOUS DRIVING VIRTUAL TEST

In this section, we introduce the overall design and process of our systematic literature review approach for autonomous driving virtual test.

# A. Overall Design

As is introduced in [16], Systematic Literature Review (SLR) is a mainstream means of understanding the latest research tools in a specific field [17]. We introduce SLA into autonomous driving survey process. Therefore, our Systematic Literature Review (SLR) approach for Autonomous Driving Virtual Test abbreviated as AuDrTeSurvey will provide

autonomous driving virtual test specific survey rules to help researchers identify and explain the available research related to collecting datasets and toolsets for autonomous driving virtual test questions. AuDrTeSurvey mainly includes searching, evaluating, explaining, and summarizing findings and trends inference from autonomous driving research. Based on the scientific process, AuDrTeSurvey can provide clear motivation for new work, and new evidence to guide decision-making using autonomous driving datasets and toolsets [18].

#### B. Process

Based on the framework in Fig.1, we now present the details of our analysis process. The key steps are highlighted as follows:

- Design research questions in autonomous driving virtual test.
- 2) Perform a knowledge map based test influencing factors analysis. First, the most critical papers are classified into sub-categories which will be denoted as Atomic Variable, Response Variable, Vehicle Settings and the relationship between variables. Then based on the first-level categories, sub-categories (or atomic factors) are derived. After these steps, a knowledge map can be formed.
- Perform a review of datasets and toolsets in autonomous driving test.
- Analyze new findings and give research trend inferences with the scenes, influence factors concerned.

Using the literature from 2000 to 2020 as an example, the analysis process and its results will be shown in the following SectionIII.

#### III. CASE STUDY DESIGN

#### A. Design of Research Questions

As our method is driven by research questions, first the general question (GQ) and the sub-questions are designed.

 GQ. How to benefit the virtual test process of autonomous driving based on the datasets and toolsets?

Next, GQ was divided into the following six research questions (RQ), and we will mark at the answer to them in full text.

- RQ1. Research from which perspective has an impact on autonomous driving testing?
- RQ2. What data sets and tools for automated driving tests are involved in the research?
- RQ3. Which test scenario variables are mainly involved in the research?
- RQ4. Which technique was used in the test?
- RQ5. What innovative discoveries or unique features did the research illustrate?
- RQ6. What are the unsolved challenges and future trends

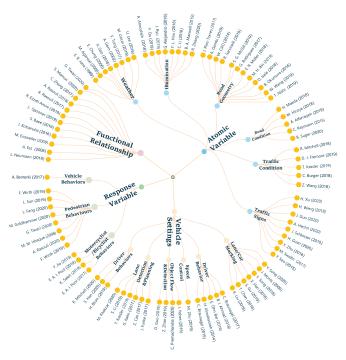


Fig. 2: Knowledge Map based Test Influencing Factors Analysis.

# B. Knowledge Map based Test Influencing Factors Analysis

Next, the latest progress of 98 papers are presented using the knowledge map (Fig.2). The 98 papers are classified into four categories which include test scene elements denoted as Atomic Variable, interaction under vehicle response denoted as Response Variable, the setting of the algorithm, technology, etc. of the test denoted as Vehicle Settings, the relationship between variables denoted as Functional Relationship to help answer general question (RQ1). Based on the categories, 15 factors are derived, together with its challenging scenes and datasets we recommended are shown in Tab.I.

# C. A Review of Scene Driven Autonomous Datasets and Toolsets

For datasets, we reviewed 70 datasets, covering basic information, open source links, data set format, size, provided markup information and other data items were taken into consideration (RQ2). Based on our analysis, a summary of autonomous test datasets with scenario and influencing factor concerned is shown in Fig.3(a).

For toolsets, we investigated 35 toolsets and included basic information, open source links, main functions, supported languages and platforms and other data items into the discussion (RQ2). A summary of autonomous test datasets with scenario and influencing factor concerned is shown in Fig.3(b).

TABLE I: Summary of Autonomous Test Datasets With Scenario and Influencing Factor Concerned

Factor (RQ3)	Challenging Scenes	Typical Datasets				
	Atomic variable					
Weather	Blizzard, Heavy fog, Torrential rain, Overcast clouds	ApolloScape, Dr(eye)ve, FLIR				
Illumination	Shadow, Night, Direct sunlight, Alternating light and dark	Daimler Urban, NightOwls, SYNTHIA				
Road geometry	Intersections, Roundabouts, Unmapped areas, Country road	Berkeley DeepDrive, UTBM Robotcar, Malaga				
Road condition	Bumpy road surface, Unmarked road, Muddy soil, Mountainous area	Road Damage, Waymo, GIDA				
Traffic condition	High-traffic, High-speed, Accident-prone intersections	Daimler Urban, Berkeley DeepDrive, KAIST Urban				
Traffic signs	Different traffic lights in different regions, Road sign, Road director, Fence	Berkeley DeepDrive, German Traffic sign, LISA Traffic Sign				
Vehicle Settings						
Lane/car marking	Broken and missing markings, Irregular lane and road shapes	ApolloScape, CULane, Interaction				
Driver behaviors	Distraction, Drowsiness	Dr(eye)ve, JAAD				
Speed control	Driving on highways or speed limit section, Sudden braking, Overtaking	Highway Workzones, KAIST Urban, NightOwls				
Opject flow &detection	Small objects moving at high speed, Flying objects, Suddenly appearing objects	Brain4Cars, DIPLECS, HighD				
Lane detection &planning	Irregular Lanes, Crossing multiple lanes, Lanes with traffic rules	CULane, NGSIIM, Argoverse				
Semantic segmentation	Difficult to capture or fuzzy mark, Road signs with cultural differences	Karlsruhe Labeled objects, SYNTHIA, LostAndFound				
	Response Variable					
Vehicle behaviors	Overtaking intention, Sudden movement, Non-compliance	Brain4Cars, UAH, Oxford RobotCar				
Pedestrian behaviours	role, Walk freely in trod, Whistle, Interactive challenge	Stanford Track, JAAD, TUM City				
Motorcyclist/ Bicyclist behaviors		Daimler Pedestrain, Road Damage, ETH Pedestrain				
	Francisco I Deletico dele					

# Functional Relationship

Functional relationship is the Interrelationships between factors. For example, Pedestrians will change their behavior as weather or car speed changes. Because there is no quantitative relationship network, plus the difficulty to build, related tests are often skipped. However, It is generally considered as the future work (RQ6). To date, some incipient studies have been carried out, as is shown in Fig.2.

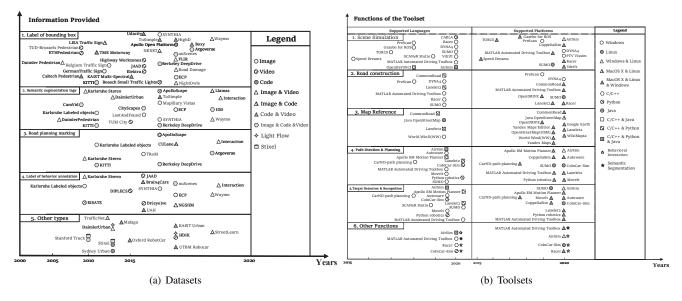


Fig. 3: Scenario Driven Autonomous Driving Datasets and Toolsets Survey

# IV. FINDINGS AND TRENDS INFERENCES

#### A. Findings and Trend Analysis: Datasets

1) Cooperated University and Industry Research Enhanced: As one of the main trend with the datasets, the datasets not only differs in scale and volume, but also tend to be relatively heterogeneous. For example, these datasets cover testing tasks in different directions, such as perception, mapping and driving strategies, and targets different urban areas, pedestrian behaviors, and scene sources. On the one hand, in the past, data sets developed by companies or schools in Europe and the United States represented as Germany MPI-IS have dominated the mainstream (59 items, 84.3% in our case) datasets.

On the other hand, recently, the cooperated university and industry research is enhanced. For example, in our study, data sets in Asia represented by Baidu's Apollo have gains increasing popularity which amounts to 11.4%.

2) Technical Trend Findings: Under the guidance of SectionI, the contribution of the datasets under three test challenges: key cases, high complexity and coverage, and interactive behavior will be discussed, so as to deal with them getting help from datasets (RQ4, RQ5).

Key Cases: Dealing with challenging scenes shown in TabI is the way to construct key cases. For example, among datasets, HCI Challenging Stereo proposed a dynamic object evaluation mask and the most extreme weather videos for the response test of the weather environment. Dr(eye)ve covers the most diverse changing weather used to train an end-to-end deep network. For rugged roads, Road Damage is the first unified road damage data set covering the most instances based on a state-of-the-art object detection method using CNN. CCSAD, CULane, etc. also provide guidance in this area. In addition, Bosch Small Traffic Lights propose a traffic light detector based on deep learning and stereo vision to

provide the most comprehensive traffic lights information for multi-vehicle interactive testing.

High Complexity and Coverage: Urban traffic scenarios are popular choice for testing with high coverage. For example, ApolloScape for urban scenes covers the most complex traffic flow videos of traffic participants based joint self-localization and segmentation algorithm. KAIST Urban covers the most diverse radar and point clouds of important features of urban environments by the SLAM algorithm. Cityscapes exploit large volumes of annotated data composed of thirty elements to train DNN. Besides, Daimler Urban, Lost&Found, JAAD, etc. are also one of the best choice under high complexity.

**Interactive Behavior**: As the key to the safety of the test [19], interactive test and datasets borrowed more and more pedestrian and driver's studies. ETH modeled the most accurate pedestrian trajectory that can be used to train DNN. Based on annotation data and attribute statistics, JAAD focuses on the most typical factors affecting people's attention. Dr(eye)re is the first dataset to record the driver's attention based on a multi-branch deep architecture. In addition, DIPLECS, Elektra, UAH, etc. also cover better interaction data.

# B. Findings and Trend Analysis: Toolsets

1) Cooperated University and Industry Research Enhanced: The combination of most tool sets and test can play a good role. As table III shows, Numerous tools used for autonomous driving have been released by many companies, such as Google Inc. and university, such as Chalmers Univ.. Although there are not publicly emphasize that these tools can be used for autonomous driving tests, as shown in Fig.3(a), these tool have wide range of uses in test.

Nowadays, As shown in Fig.3(b), the simulation platform is the most popular function (19 items, 54.3%). In

TABLE II: Scenario Driven Autonomous Driving Datasets Survey

Time	Dataset	Volume	Time	Dataset	Volume	Time	Dataset	Volume
2020	Interaction	multiple vary	2017	Bosch Small Traffic Lights	13K Image	2013	AMUSE	7 Video, 1.2TB
2020	NGSIIM	multiple vary	2017	DAVIS	41 Video, 450GB	2013	Daimler Urban	5K stereo Image
2019	Argoverse	300K Video	2017	Mapillary Vistas	25K Image	2013	Stixel	2.5K Image, 3GB
2019	Boxy	200K Image	2017	NEXET	55K Image. 10GB	2013	Sydney Urban	200MB
2019	IDD	10K Image	2017	SYNTHIA	200K Image	2012	German Traffic Sign	5K Image, 1.6GB
2019	Llamas	100K Image	2017	TuSimple	5K Video	2012	HCI Challenging Stereo	11 Video
2019	StreetLearn	114K Image	2016	Brain4Cars	700 Video	2012	LISA Traffic Sign	6.6K Image, 8GB
2019	Waymo	multiple vary	2016	CityScapes	25K Image, 63GB	2012	TrafficNet	10.3GB
2018	Apollo Open Platform	multiple vary	2016	Comma.ai	80GB	2011	Belgium Traffic Sign	9K Image, 50GB
2018	ApolloScape	114K Image	2016	Daimler Pedestrian	2.5MB~45GB each	2011	CMU	16 Video, 275GB
2018	Comma2k19	2019 Video, 100GB	2016	Dr(eye)ve	74Video, 555K Image	2011	Karlsruhe Labeled Objects	1K Image, 631MB
2018	CULane	133K Image	2016	Elektra	9 datasets, 0.5GB~12GB each	2011	KITTI	multiple vary
2018	DBNet	10K Image	2016	GIDA	multiple vary	2011	TME Motorway	28 Video
2018	ECP	43K Image	2016	JAAD	347 Video, 170GB	2010	Cheddar Gorge	329GB Video
2018	FLIR	14K Image	2016	Lost & Found	2K Image, 40GB	2010	EISATS	multiple vary
2018	HDIK	1K Image	2016	TRoM	700 Image	2010	Karlsruhe Stereo	20 Image sequence
2018	HighD	147h Video	2016	UAH	35 Video	2010	Stanford Track	14K tracks, 5.7GB
2018	KAIST Urban	19Video, 1GB∼22GB each	2016	Udacity	300GB	2009	Caltech Pedestria	250K Image, 11GB
2018	NightOwls	279K Image	2015	DIPLECS	4.3GB & 1.1GB	2009	CamVid	700 Image, 8GB
2018	nuScenes	1K Video, 1.4M Image	2015	HighWay Workzones	6 Video, 1.2GB	2009	ETH Pedestrian	4.8K Image, 660MB
2018	Road Damage	9K Image	2015	KAIST Multi-Spectral	10 Video	2009	Ford	2datasets, 78GB & 119GB
2018	TUM City	73GB & 1.1GB	2015	Oxford RobotCar	130 Video, 23TB	2009	TUD Brussels Pedestrian	1.6K Image
2018	UTBM Robotcar	11 Video	2014	CCSAD	96K Image, 50GB			
2017	Berkeley DeepDrive	100K Image, 1.8TB	2014	Malaga	15 Video, 70GB			

addition, Path detection (12 items, 34.2%) and Map-based road network construction (11 items, 31.4%) also plays an important role. For example, PreScan, Google Earth long-term performed well, Airsim is the rise of this field.

2) Technical Trend Findings: Under the guidance of Section II, three toolset hot spots: simulated scenes diversity and authenticity, road network generation, and motion planning, which reveal the technical challenges of setting up tests: scenario simulation, road network generation, and trajectory planning, will be be discussed to provide assistance in solving above chanllenge (RO4, RO5).

**Simulated Scenes Diversity and Authenticity**: Highquality sensors, multivariate variables, real-time environments, and real-time response are the key in this area. For example, CoppeliaSim, PreScan are equipped with the most excellent sensors to respond. SCANeR Stutio covers the Most diverse environment scenes, including terrain, pedestrians, etc.,and DYNA4 has the best effect in the simulation of scenes such as lanes. TORCS, Speed Dreams, and Open-DaVINCI perform best in real-time respond. In addition, cross-domain research has also been introduced to the test, such as the drone simulator AirSim, and the game GTA.

**Road Network Generation**: Map, Descriptive low-level tools, and Simulator developed on the underlying file is the key in this area. For example, OpenStreetMap provides the most time-efficient and accurate world map reference. OpenDRIVE is the most efficient and underlying foundation for road network tools, Lanelet2 has the best open-access motion planning solution, and CommonRoad has a set of public road network scenarios covering traffic data. AutoSim

TABLE III: Scenario Driven Autonomous Driving Toolsets Survey

Time	Toolset	Provider	Time	Toolset	Provider	Time	Toolset	Provider
2020	AirSim	Microsoft Inc.	2020	MATLAB AD Toolbox	The MathWorks	2020	Yandex Maps Editior	Yandex Inc.
2020	Apollo EM Motion Planner	Baidu Inc.	2020	Movelt	PICKNIK Inc.	2019	OpenDRIVE	ASAM
2020	Autoware	Tier IV Inc.	2020	OpenStreetMap	OpenStreetMap	2019	PreScan	SIEMENS
2020	CARLA	CVC, Spain	2020	PTV Vissim	PTV Group	2019	SCANeR Stutio	AVSimulation Inc.
2020	CarMaker	IPG Inc.	2020	Python robotic	Atsushi Sakai	2018	AutoSim	NVIDIA
2020	CoInCar-Sim	KIT Univ.	2020	Racer	Cruden Inc.	2018	CarND-path planning	Jeremy Shannon
2020	CommonRoad	TUM Univ.	2020	SUMO	OpenMobility Group	2018	Gazebo for ROS	Open Robotic
2020	CoppeliaSim	Coppelia Robotics Inc.	2020	VDrift	VDrift Group	2017	ASM Traffic	dSpace Inc.
2020	DYNA4	Vector Inc.	2020	VTD	VIRES, Germany	2017	OpenDaVINCI	Chalmers
2020	Google Earth	Google Inc.	2020	WikiMapia	WikiMapia Group	2017	TORCS	SOURCEFORG
2020	Java OpenStreetMap	Trac Inc.	2020	World Wind(WW)	NASA	2015	Speed Dreams	SOURCEFORG
2020	Lanelet2	CVC, Spain	2020	Yandex Map	Yandex Inc.			

analyzed the OpenStreetMap to generate the most simulated 3D road network. Moreover, DYNA4 and MATLAB Automated Driving also contributes better in this area.

Motion Planning: Nowadays, Taking traffic rules and the intervention of pedestrian into account is popular in motion planning. For example, CoInCar-Sim provides better vehicle trajectory planning program based on the framework of interaction between traffic participants and traffic rules. Apollo EM Motion Planner provides More efficient trajectory schemes under the framework of safety and scalability. CarMaker designed a better simulation solution and semantic recognition of traffic signs to contributes to this area.

# V. CONCLUSION

In this paper, we proposed the first systematic literature review method for autonomous driving virtual test, and presents a survey of the perspectives and trends of both datasets and toolsets for autonomous driving virtual test. Quantitative findings with the scenarios concerned, perspectives and trend inferences and suggestions with 35 automated driving test tool sets and 70 test data sets are also presented. Our future work includes the wide applications of the datasets and toolsets to our virtual tests.

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