Literature Review-文献综述

写在前面

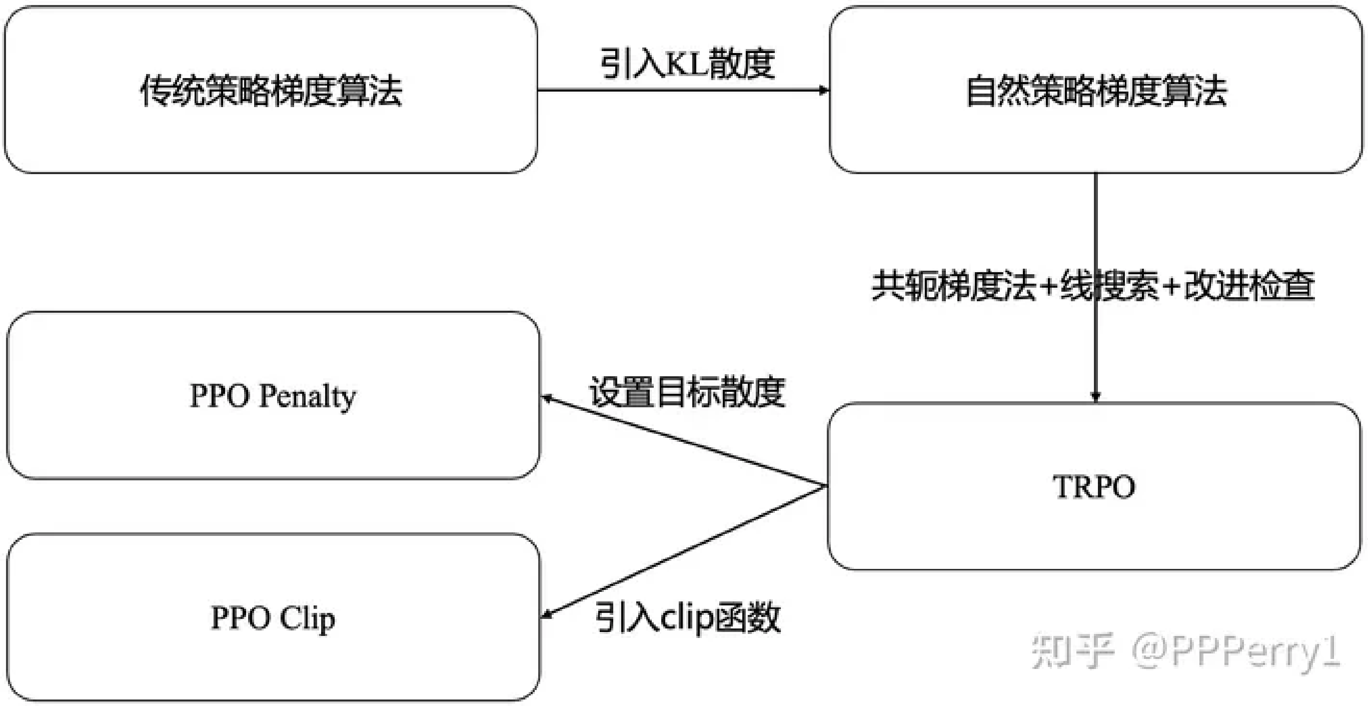
对于这个我刚刚开始接触的领域, 即使它和之前的无人机系统有许多相似的研究方向, 我仍然不清楚应该怎么去验证自己所提出的方向(**PPO路径规划算法-动态奖励函数设计**)的可行性, 于是开始从文献综述开始.
文献综述的目的是了解这一领域大家都是怎么做的, 需要了解哪些方法, 哪些是重点.
我打算先网上找一些现成的文献综述, 其次是自己找一些相关论文补充进去.

Update 04/12/2023

Proximal Policy Optimization Algorithm

[12.4_literature_review.pdf]

近端策略优化算法是OpenAI在2017年提出的一种强化学习算法



1. 传统策略梯度算法
2. 自然策略梯度算法
3. 信赖域策略优化算法TRPO
4. 近端策略优化算法PPO

从传统策略梯度算法，到自然策略梯度算法，再到TRPO算法，以及最终的PPO算法，经过不断的优化迭代，PPO算法已经成为强化学习领域最主流的算法。不论是学术界中的各大顶会文章，还是工业界中例如chatgpt的背后强化学习部分的实现，都离不开PPO算法的身影。

纵向来看，对策略梯度算法的改进，主要针对的就是**限制参数迭代**的这一步。
自然策略梯度算法引入了KL散度约束，TRPO利用线搜索和改进检查来保证限制下的可行性，PPO则通过clip函数限制了策略可以改变的范围等。

相比于自然梯度和TRPO所具有的理论保证和数学技巧，PPO放弃了一些数学上的严谨性，但往往能比其竞争对手更快更好地收敛。看来PPO在速度、严谨性和可用性之间取得了正确的平衡，在未来几年来依旧会保有属于它的竞争力。

Update 01/01/2024 17:00

1. [Milestones in Autonomous Driving and Intelligent Vehicles: Survey of Surveys]

这篇文章选择了122篇调查文献, 涵盖了无人驾驶的多个领域, 比较全面. 对未来的预期主要分为以下几个部分:
A. Independent Tasks

1. Perception
2. Planning
3. Control
4. Testing
5. Human Behaviors

B. Ethics on Autonomous Driving

1. Normative Ethics
2. Environmental and Public Health Ethics
3. Business Ethics

C. Future Directions:

1. Human-Machine Hybrid Intelligence
2. Parallel Intelligence in Autonomous Driving
3. From Scenario Enginnering to Scenario Intelligence

Fig. 1. We provide all the collected papers on the time axis with abbreviations, consisting of the categories, published journals and the serial number.

TABLE III
THE DATASETS ON THE AUTONOMOUS DRIVING[1]

Dataset	Frame	Sensors							Task																	
		Li	Vi	Ra	GP	IM	Ca	Te	Sc	Od	La	Dr	2D	3D	Di	OF	SF	PS	Se	Pa	De	Tr	Pr	Pl	E2E	HD
KITTI [123]	15K	1	2	-	1	1	-	-		✓			✓	✓	✓	✓	✓		✓	✓	✓	✓				
CityScapes [124]	25K	-	2	-	1	1	-	1					✓	✓					✓	✓						
nuScenes [134]	40K	1	6	5	1	1	-	-					✓	✓				✓		✓		✓	✓			
A2D2 [129]	12K	5	6	-	1	-	-	-					✓	✓				✓	✓							
Lyft L5 [135]	-	3	7	-	-	-	-	-						✓									✓			
A*3D [127]	39K	1	2	-	-	-	-	-					✓	✓												
ApolloScape [136]	144K									✓	✓		✓	✓	✓			✓	✓		✓	✓		✓		
BDD100K [125]	100K	-	1	-	1	1	-	-	✓			✓	✓						✓	✓		✓				
H3D [128]	27K	1	-	-	1	1	1	-						✓								✓				
Argoverse [137]	22K	2	9	-	1	-	-	-					✓	✓	✓						✓	✓	✓			✓
Mapillary Vistas [126]	25K	1	1	-	1	-	-	-		✓			✓	✓				✓	✓	✓	✓				✓	
Waymo Open [138]	200K	5	5	-	-	-	-	-					✓	✓				✓	✓	✓		✓				
Comma2k19 [139]	200K	-	1	-	1	1	1	-		✓	✓									✓						
Ford Dataset [130]	200K	4	7	-	1	1	-	-		✓			✓	✓												
PandaSet [140]	16K	2	6	-	1	1		1			✓	✓					✓									
ONCE [141]	1M	1	7	-	-	-	-	-					✓	✓												
AutoMine [142]	18K	1	2	-	1	1	-	-		✓			✓	✓												

[1] Li-LiDAR, Vi-Vision, Ra-Radar, GP-Global Positioning System, IM-Inertial Measurement Unit, Ca-CAN data, Te-Temperature data, Sc-Scene Classification, Od-Odometry, La-Lane Detection, Dr-Driveable Detection, 2D-2D Object Detection, 3D-3D Object Deteciton, Di-Disparity, OF-Optical Flow Estimation, SF-Scene Flow Estimation, PS-Point Segmentation, Se-Semantic Segmentation, Pa-Panoptic Segmentation, De-Depth Estimation, Tr-Tracking, Pr-Prediction, Pl-Planning, E2E-End-to-End, HD-High Definition map.

2. [Motion Planning for Autonomous Driving: The State of the Art and Future Perspectives]

这篇文章主要涉及**pipeline**和**端到端**方法，从四个方面对端到端方案的挑战和期望进行了总结，其中挑战主要是感知传感器容易受影响，规划在复杂或不确定环境下求解的困难，自动驾驶系统受到黑客攻击的安全性，数据仿真和真是环境的差异性这四个方面.

文章对市面上主要的三类端到端方法包括平行学习，强化学习和模仿学习都进行了回顾，对主流的数据集和仿真平台进行了介绍.

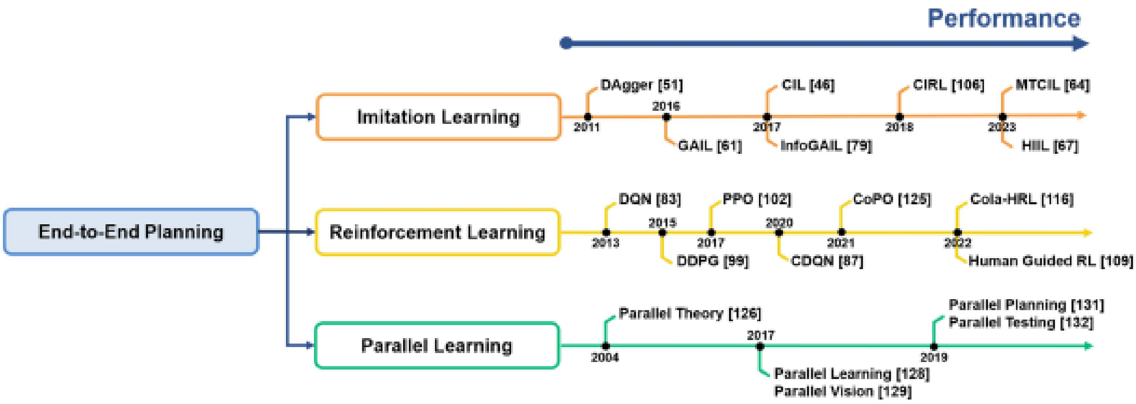


Fig. 2. Critical method survived in End-to-End Planning Section. The time axis (dark blue) represents the progressiveness of the survived methods, and the performance of the methods is better with the latter proposed time.

TABLE I
THE CRUCIAL REVIEWS AND RELATIVE INFORMATION OF EACH FAMOUS END-TO-END MODELS IN AUTONOMOUS DRIVING

Article	Category	Input	Output	Implement Tasks	Auxiliary Method	Dataset
Bojarski et al. [45]	**BC**	monocular image	steering angle	lane Keeping	CNN is the only component of end-to-end model	physical & simulate platform
Codevilla et al. [46]	**BC**	monocular image	control information	simulation navigation task	High-level commands as a switch to select the branch	Carla
Chen et al. [47]	**BC**	monocular image	control information	simulation navigation task	Affordance is used to predict control actions	TORCS Dataset & KITTI
Sauer et al. [48]	**BC**	monocular video & directional input	control information	physical navigation task	Conditional affordance is trained to calculate intermediate representations	Carla
Zeng et al. [49]	**BC**	Lidar data & HD Map	trajectory, scenario representation	physical navigation task	The intermediate representation is used to improve the model's interpretability	physical dataset collected in North America
Sadat et al. [50]	**BC**	Lidar data & HD Map	trajectory, scenario representation	physical navigation task	A joint system with interpretable intermediate representations for E2E planner	physical dataset collected in North America
Ross et al. [51]	**DPL**	monocular image	control information	autonomous racing competition	An iterative algorithm is proposed to guarantee the performance in corner cases	3D racing simulator
Zhang et al. [52]	**DPL**	monocular image	control information	autonomous racing competition	Embedded query-efficient model to reduce the request for expert trajectories	racing car simulator
Yan et al. [53]	**DPL**	LiDAR, ego-vehicle speed, Sub-goal	control information	physical & simulation navigation task	The novice and the expert policy is fused to control the robot	physical and simulate platform
Li et al. [54]	**DPL**	monocular image & sub-goal	waypoint, control information	autonomous racing	A reward-based online method learns from multiple experts	Sim4CV
Ohn-Bar et al. [55]	**IRL**	monocular image	control information	simulation navigation task	Scenario context is embedded into the policy learning network	Carla
Levine et al. [56]	**IRL**	BEV image	control information	keep the lane, change lanes & takeover	The Gaussian algorithm is used to learn the relevance of features in expert trajectories.	Highway driving simulator
Brown et al. [57]	**IRL**	monocular image	control information	keep the lane, change lanes & takeover	The high-confidence upper bounds on the $alpha$-worst-case are embedded into the policy network.	Highway driving simulator
Palan et al. [58]	**IRL**	monocular image	control information	keep the lane, change lanes & takeover	A globally normalized reward function is constructed.	Lunar lander simulator
Ziebart et al. [59]	**IRL**	Road network, Sub-goal, & GPS Data	control information	long range autonomous navigation task	A probabilistic approach is proposed for maximum entropy	Driver route modeling
Lee et al. [60]	**IRL**	monocular image	control information, costmap	keep the lane, change lanes & takeover	The query generation process is used to improve the generalization	NGSIM & Carla
Ho et al. [61]	**IRL**	monocular image	control information	keep the lane, change lanes & takeover	GAN is integrated into the end-to-end model	Carla
Phan et al. [62]	**IRL**	BEV image, HD map, obstacle information	Control information	physical navigation task	A three-step IRL planner is proposed	physical dataset from the Las Vegas Strip

TABLE IV

DATASETS AND RELATED DESCRIPTIONS FOR THE AUTONOMOUS DRIVING DATASET

Dataset	Year	Sensors	Scenarios
KITTI [143]	2013	4 cameras; 1 LiDAR	City; Countryside; Highway
Comma.ai [144]	2016	1 monocular camera; 1 point grey camera	Highway scenarios
Oxford RobotCar [145]	2016	6 Cameras; 3 LiDARS; Speed; GPS; INS	City; Contain weather changed
Mapillary Vistas [146]	2017	Image devices	Street Scenarios
nuScenes [147]	2019	6 Cameras; 5 Radars; 1 LiDAR	Street Scenarios
ApolloScape [148]	2019	2 Cameras; 2 LiDAR; GPS; IMU	Street Scenarios
Waymo Open Dataset [149]	2019	5 Cameras; 5LiDAR;	1150 Street Scenarios
BDD100K [150]	2020	1 Camera; GPS; IMU	Street scenarios in 4 cities
A2D2 [151]	2020	6 Cameras; 5 LiDAR; GPS; IMU	360° Street Scenarios
Automine [152]	2021	2 Cameras; 1 LiDAR; GPS; IMU	The first open-pit mine dataset
AI4MARS [153]	2021	2 Cameras	The first large-scale dataset in Mars
SODA10M [154]	2021	1 Camera	City Scenarios in 31 cities with all kinds of weathers
SUPS [155]	2022	6 Cameras; 1 LiDAR; GPS; IMU	Underground parking scenarios
DRIVERTRUTH [156]	2022	1 Camera; 1 LiDAR; GPS; IMU; Control signal	City Scenarios based-on CARLA
ROAD [157]	2023	1 Camera	Scenarios in [145] for road event detection

TABLE V

SIMULATION PLATFORMS AND RELATED DESCRIPTIONS FOR AUTONOMOUS DRIVING BASED ON VISUAL PERCEPTION

Platform	Latest Version	Description
PTV Vissim	V2023	Traffic simulation platform focused on complex intersection design and active traffic management.
VTD	V2.2 (19.01)	Provides a complete bottom-up simulation platform, including ADAS and automation systems.
SUMO [159]	V1.15.0 (22.11)	Provides a purely microscopic traffic model that can be defined to customize each vehicle.
TORCS	V1.3.8 (17.03)	Support for running a large number of agents at the same time, allowing for scheduling functions in dense vehicle areas.
SVL Simulator [164]	V2021.3 (21.05)	Enables developers to simulate billions of miles and arbitrary corner cases to accelerate algorithm development and system integration.
V-Rep	V3.6.2 (19.01)	With a driving actions assessment function, which indicates the agent behavior based on the result.
CarMaker	V10.0 (21.10)	Specifically designed for the development and seamless testing of cars and light-duty vehicles in all development stages.
CARLA [161]	V0.9.13 (21.11)	Various city maps are provided for autonomous driving algorithms, as well as support for customized sensor types and weather conditions.
AriSim [165]	V1.8.1 (22.06)	The capability to quickly complete autonomous driving tests, and build various scenarios (urban, countryside, highway, field, etc.)
Apollo [148]	V8.0 (22.12)	Support for learning and validation of single and multi-vehicle autonomous driving algorithms on urban scenarios.
Autoware [160]	V1.11.0 (21.05)	An open-source autonomous driving platform, which include all component of autonomous function for intelligent vehicle.
Drive Constellation	V6.05 (22.10)	Provides a computing platform based on two different servers that can undertake large-scale vehicle data interaction services.
MetaDrive [163]	V0.2.6.0 (22.11)	A wide range of road segments are available, which can be customized to generate a variety of complex scenarios, more suitable for reinforcement learning.

3. Recent Advancements in End-to-End Autonomous Driving using Deep Learning: A Survey

这篇文章也是对端到端方法的综述, 和上一篇文章类似也对各种端到端方法，经典的数据集和仿真软件进行了回顾，但是各有侧重，两篇文章可以互相补充一起看。

Table 4
END-TO-END DRIVING TESTING TO ENSURE SAFETY

Methods	Summary	Literature
Search-based testing	Generating neuron coverage to identify false actions	[120]
	Designing an diverse and critical unsafe test cases	[6]
	Objective function to search safety sensitive output	[84]
Optimization-based attack	Place the original object with an adversarial one	[103]
	Virtual obstacles to generate adversarial attack in natural environment	[22]
GAN-based attack	Generate the adversarial realistic-looking representations based on images	[121]
	Generate pedestrian augmentation from inserting pedestrians in image	[122]
	Designing an objective function to search for the diverse unsafe test cases	[8]

Table 7
CARLA AUTONOMOUS DRIVING LEADERBOARD 1.0 SUBMISSION UNTIL AUGUST 2023

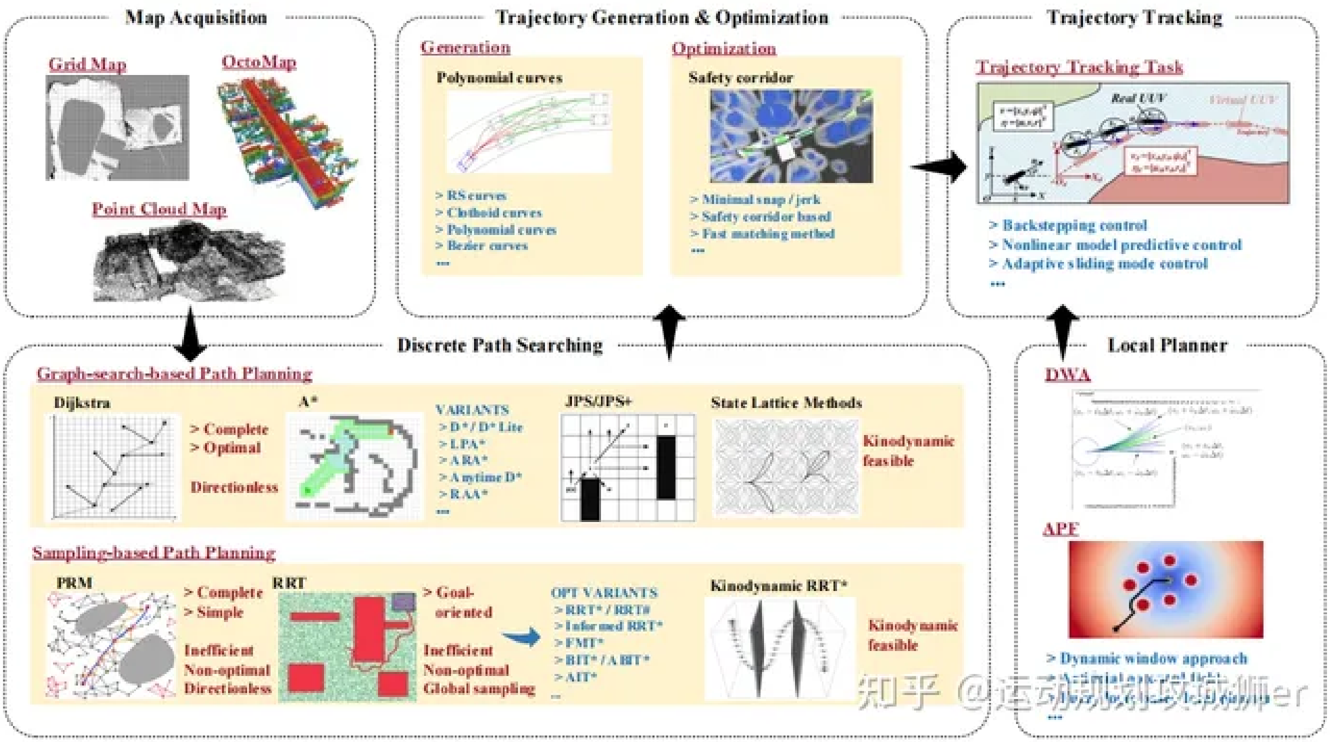
Rank	Submission	DS	RC	IP	CP	CV	CL	RLI	SSI	OI	RD	AB	Type
		%	%	[0,1]	infractions/km								E/M
1	ReasonNet [16]	79.95	89.89	0.89	0.02	0.13	0.01	0.08	0.00	0.04	0.00	0.33	E
1	InterFuser [8]	76.18	88.23	0.84	0.04	0.37	0.14	0.22	0.00	0.13	0.00	0.43	E
2	TCP [13]	75.14	85.63	0.87	0.00	0.32	0.00	0.09	0.00	0.04	0.00	0.54	E
3	TF++ [71]	66.32	78.57	0.84	0.00	0.50	0.00	0.01	0.00	0.12	0.00	0.71	E
3	LAV [10]	61.85	94.46	0.64	0.04	0.70	0.02	0.17	0.00	0.25	0.09	0.10	E
4	TransFuser [7]	61.18	86.69	0.71	0.04	0.81	0.01	0.05	0.00	0.23	0.00	0.43	E
5	Latent TransFuser [7]	45.20	66.31	0.72	0.02	1.11	0.02	0.05	0.00	0.16	0.00	1.82	E
6	GRIAD [100]	36.79	61.85	0.60	0.00	2.77	0.41	0.48	0.00	1.39	1.11	0.84	E
7	TransFuser+ [7]	34.58	69.84	0.56	0.04	0.70	0.03	0.75	0.00	0.18	0.00	2.41	E
8	World on Rails [99]	31.37	57.65	0.56	0.61	1.35	1.02	0.79	0.00	0.96	1.69	0.47	E
9	MaRLn [53]	24.98	46.97	0.52	0.00	2.33	2.47	0.55	0.00	1.82	1.44	0.94	E
10	NEAT [12]	21.83	41.71	0.65	0.04	0.74	0.62	0.70	0.00	2.68	0.00	5.22	E
11	AIM-MT [12]	19.38	67.02	0.39	0.18	1.53	0.12	1.55	0.00	0.35	0.00	2.11	E
12	TransFuser [14]	16.93	51.82	0.42	0.91	1.09	0.19	1.26	0.00	0.57	0.00	1.96	E
13	CNN-Planner [143]	15.40	50.05	0.41	0.08	4.67	0.42	0.35	0.00	2.78	0.12	4.63	M
14	Learning by [48]	8.94	17.54	0.73	0.00	0.40	1.16	0.71	0.00	1.52	0.03	4.69	E
15	MaRLn [53]	5.56	24.72	0.36	0.77	3.25	13.23	0.85	0.00	10.73	2.97	11.41	E
16	CILRS [12]	5.37	14.40	0.55	2.69	1.48	2.35	1.62	0.00	4.55	4.14	4.28	E
17	CaRINA [144]	4.56	23.80	0.41	0.01	7.56	51.52	20.64	0.00	14.32	0.00	10055.99	M

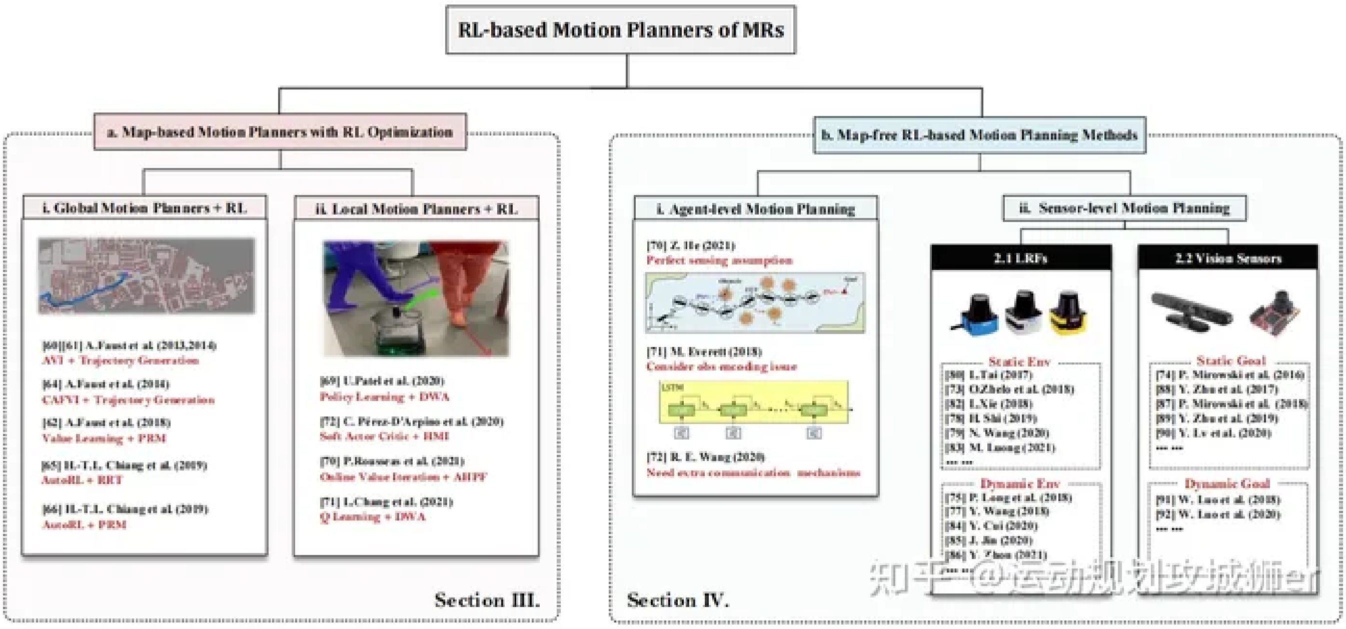
Route Completion (RC), Infraction Score/penalty (IS), Driving score (DS), Collisions pedestrians (CP)/(PC), Collisions vehicles (CV), Collisions layout (CL)/(LC), Red light infractions (RLI), Red light violation (RV), Stop sign infractions (SSI), Off-road infractions (OI), Route deviations (RD), Agent blocked (AB), End-to-End Architecture (E), Modular Architecture (M).

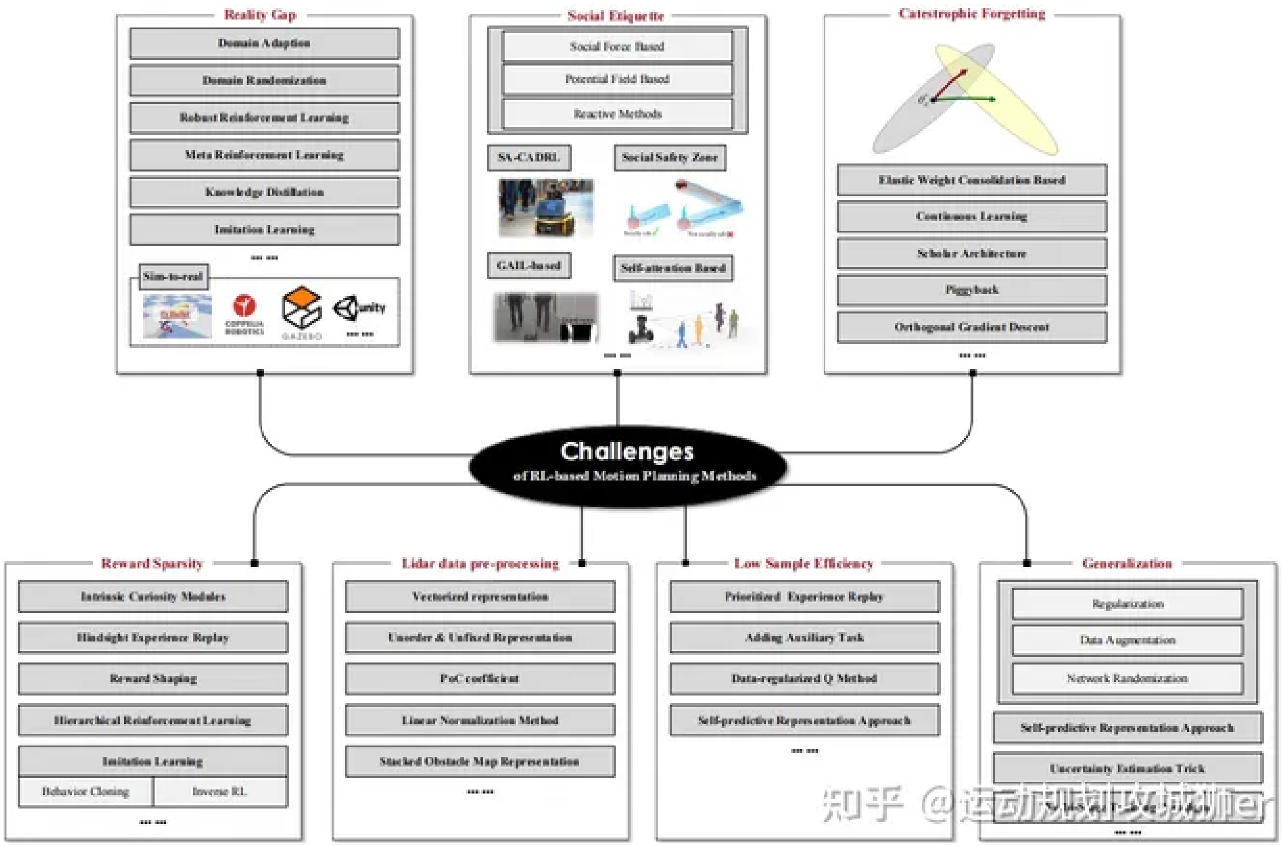
Datasets	Year	Sensors Modalities							Content			Weather			Size	Location	License
		Cameras	LiDAR	GNSS	Steering	Speed, Acceleration	Navigational command	Route planner	Obstacles	Traffic	Roads	Sunny	Rain	Snow or Fog			
Udacity [124]	2016	✓	✓	✓	✓	✓			✓	✓		✓			5h	Mountain View	MIT
Drive360 [125]	2019	✓		✓	✓	✓		✓	✓			✓	✓		55h	Switzerland	Academic
Comma.ai 2016 [126]	2016	✓		✓	✓	✓						✓			7h 15min	San Francisco	CC BY-NC-SA 3.0
Comma.ai 2019 [127]	2019	✓		✓	✓	✓						✓			30h	San Jose California	MIT
DeepDrive-BDD 100 [128]	2018	✓		✓					✓	✓		✓	✓		1100h	US	Berkley
Oxford RobotCar [2]	2019	✓	✓	✓					✓	✓		✓	✓	✓	214h	Oxford	CC BY-NC-SA 4.0
HDD [129]	2018	✓	✓	✓	✓	✓	✓		✓	✓	✓				104h	San Francisco	Academic
Brain4Cars [130]	2016	✓		✓		✓			✓	✓					1180 miles	US	Academic
Li-Vi [131], [132]	2018	✓	✓	✓	✓	✓									10h	China	Academic
DDD17 [133]	2017	✓		✓	✓	✓			✓	✓		✓	✓		12h	Switzerland, Germany	CC-BY-NC-SA-4.0
A2D2 [134]	2020	✓	✓	✓	✓	✓			✓	✓		✓			390k frames	South of Germany	CC BY-ND 4.0
nuScenes [122]	2019	✓	✓	✓					✓			✓	✓		5.5h	Boston, Singapore	Non-commercial
Waymo [135]	2019	✓	✓	✓	✓	✓			✓			✓			5.5h	California	Non-commercial
H3D [30]	2019	✓	✓	✓	✓	✓						✓			N/A	Japan	Academic
HAD [136]	2019	✓		✓	✓	✓	✓			✓					30h	San Francisco	Academic
BIT [137]	2015	✓							✓			✓			9850 frames	Beijing	Academics
UA-DETRAC [138]	2015	✓							✓			✓			140k frames	Beijing, Tianjing	CC BY-NC-SA 3.0
DFG [139]	2019	✓								✓		✓	✓		7k+8k	Slovenia	CC BY-NC-SA 4.0
Bosch [140]	2017	✓								✓		✓			8334 frames	Germany	Research Only
Tsinghua-Tencent 100k [141]	2016	✓								✓		✓			30k	China	CC-BY-NC
LISA [142]	2012	✓								✓		✓			20k	California	Research Only
STSD [143]	2011	✓								✓		✓			2503 frames	Sweden	CC BY-SA 4.0
GTSRB [144]	2013	✓								✓		✓	✓		50k	Germany	CC0 1.0
KUL [145]	2013	✓								✓		✓			16k	Flanders	CC0 1.0
Caltech [146]	2009	✓							✓			✓			10 hours	California	CC4.0
CamVid [147]	2009	✓							✓	✓	✓	✓			22 min, 14 s	Cambridge	Academic
Ford [148]	2018	✓	✓						✓			✓			66 km	Michigan	CC-BY-NC-SA 4.0
KITTI [99]	2013	✓	✓	✓					✓	✓	✓	✓			43 k	Karlsruhe	Apache License 2.0
CityScapes [149]	2016	✓		✓					✓	✓		✓			20+5 K frams	Germany, France, Scotland	Apache License 2.0
Mapillary [150]	2017	✓							✓			✓	✓	✓	25000 frames	Germany	Research Only
ApolloScape [123]	2018	✓	✓						✓	✓		✓	✓	✓	[illegible]	[illegible]	[illegible]
VERI-Wild [151]	2019	✓							✓			✓	✓		[illegible]	[illegible]	[illegible]
D2-City [152]	2019	✓							✓		✓	✓	✓		10000 video	China	Research Only
DriveSeg [153]	2020	✓							✓	✓	✓	✓			500 minutes	Massachusetts	CC BY-NC 4.0

4. A Review of Mobile Robot Motion Planning Methods: from Classical Motion Planning Workflows to Reinforcement Learning-based Architectures

和前面的文章不同，这篇文章并不针对于车辆而是所有移动机器人领域。另外这篇文章虽然也是从传统方法回顾到深度学习方法，但更加侧重于对强化学习方法的总结。作者认为基于强化学习的方法主要分为使用了强化学习策略改进的运动规划方法、不依赖地图的基于强化学习的运动规划方法和多机器人协同规划方法这三种。最后对基于强化学习的运动规划方法存在的奖励稀疏性问题、样本效率低、泛化问题、情景遗忘问题和激光雷达数据预处理问题进行了分析和展望。







5. A Survey of Trajectory Planning Methods for Autonomous Driving – Part I: Unstructured Scenarios

这篇文章主要聚焦于非结构化场景，全文基本上将所有经典的适用于非结构化场景的方法都回顾了一下. 不仅从理论上对各个方法的优缺点和计算复杂度进行了对比，还做了实验甚至给出了源代码.

1. 传统的针对机器人轨迹规划方法不适用于自动驾驶轨迹规划，后者由于包含了非完整的运动学约束其计算复杂度要比机器人的方法难得多。
2. 目前最推荐的碰撞检查方式是基于占用网格图的碰撞检查方法，与AABB和OBB等其他碰撞检查方法相比，这种方法耗时最短并且其耗时和障碍物数量多少关系不大。

3. 在非结构化环境中最推荐的运动规划方法是两阶段的基于优化的算法，其中第一阶段应该使用关键变量优化搜索来得到初始解，第二阶段应该使用CFS方法处理碰撞躲避约束，用L1范数行驶的代价函数来处理非线性的运动约束。这种算法可以充分利用第一阶段搜索方法速度快的优点以及第二阶段数值优化质量高的优点，因此可以快速找到高质量的可行轨迹。

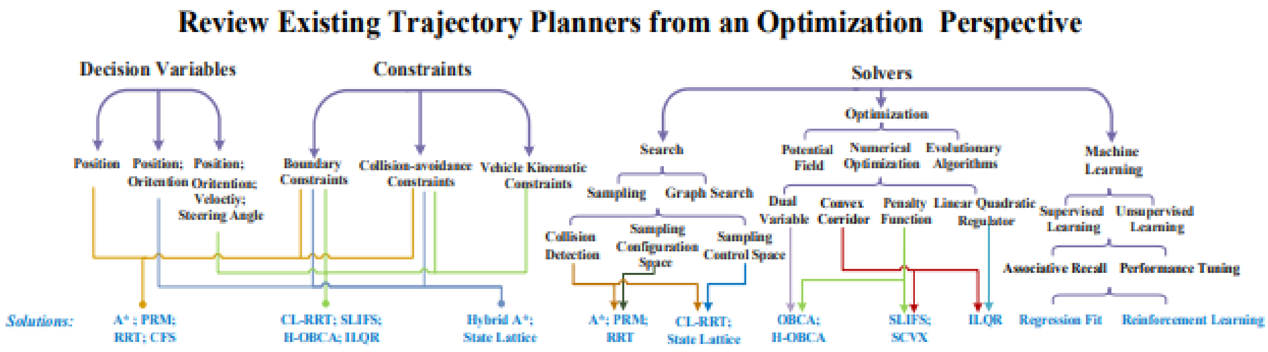


TABLE XIV. COMPARISONS AMONG TRAJECTORY PLANNING LIBRARIES

Library	Coding Language	Content	Embedded Functions	Applications
SBPL	MATLAB C++	Search-based planners with primitives	Collision check × Kinematic feasibility check × Visualization ×	Robotic arm Intelligent vehicles
OMPL	Python C++	Search-based planners with primitives, search-based planners with random sampling	Collision check √ Kinematic feasibility check × Visualization ×	Robotic arm
CHOMP	C++	Covariant Hamiltonian optimization method for motion planning	Collision check × Kinematic feasibility check × Visualization ×	Robotic arm
STOMP	C++	Stochastic trajectory optimization method for motion planning	Collision check × Kinematic feasibility check × Visualization ×	Robotic arm
Trajopt	Python C++	Sequential convex optimization method	Collision check √ Kinematic feasibility check √ Visualization √	Robotic arm
PythonRobotics	Python MATLAB	Search-based planners with primitives, search-based planners with random sampling, sampling-based planners, potential field-based planners, spline-based planners	Collision check √ Kinematic feasibility check × Visualization √	Robotic arms Holonomic wheeled robots Intelligent vehicles
Autoware	C++	Search-based planners with primitives	Collision check √ Kinematic feasibility check √ Visualization √	Intelligent vehicles driving in structured (major) and unstructured (minor) environments
Apollo	C++	Search-based planners with primitives, search-based planners with random sampling, sampling-based planners, optimization-based planners, learning-based planners	Collision check √ Kinematic feasibility check √ Visualization √	Intelligent vehicles driving in structured (major) and unstructured (minor) environments
CommonRoad	Python	Search-based planners with primitives, Interfaces to learning-based planners	Collision check √ Kinematic feasibility check √ Visualization √	On-road intelligent vehicles
This work	MATLAB Python C++	Search-based planners with primitives, search-based planners with random sampling, sampling-based planners, optimization-based planners, learning-based planners	Collision check √ Kinematic feasibility check √ Visualization √	Intelligent vehicles driving in unstructured environments

6. Chaotic Motion Planning for Mobile Robots: Progress, Challenges, and Opportunities

这篇文章主要是对混沌运动规划算法进行了回顾介绍。混沌规划算法是一种基于混沌理论的规划方法。它通过引入随机性和非线性特征来模拟真实世界的复杂性。因此此类方法理论上可以覆盖所有包含静态或动态障碍的场景。这类方法不是很常见，这篇文章较为系统地回顾总结了这类方法的优缺点以及未来发展的趋势，可以作为一篇入门文章来学习。

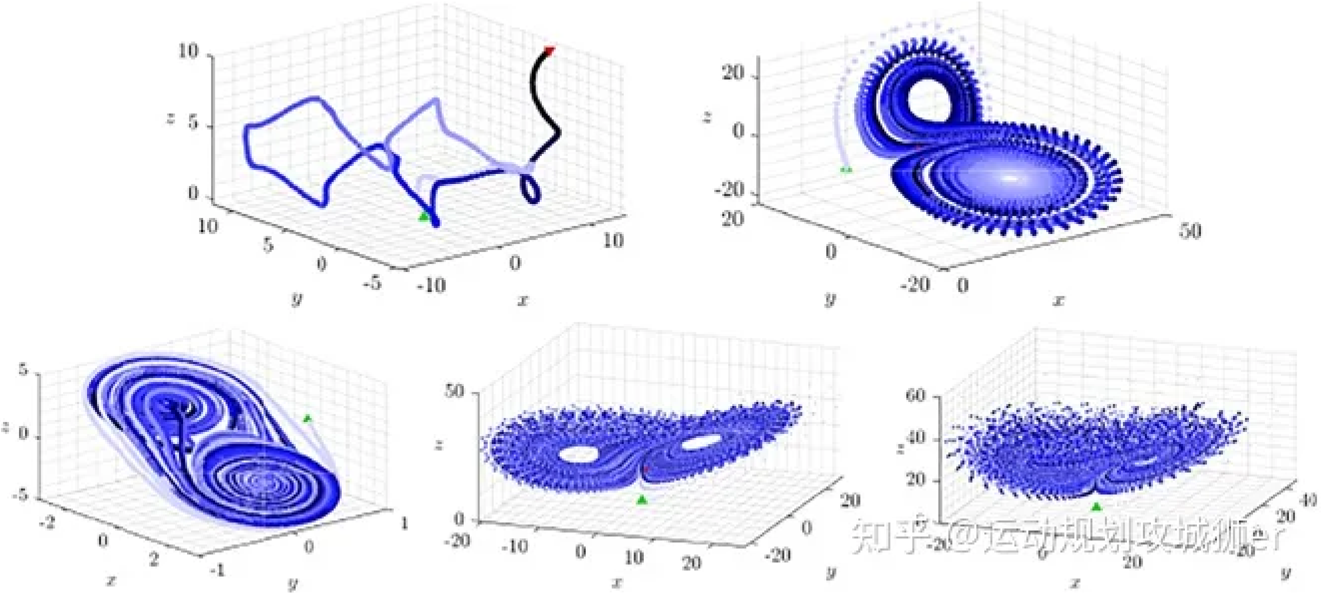

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TABLE 1. Performance comparison between chaotic coverage path planners.

Ref.	CDS	Method	Sim/Exp	CT (s)	A_{TC} (m^2)	A_D (m^2)	v (m/s)	$CR(\%)$	$Obs_o(\%)$	N_R	PM
1.[121]	Arnold	NA	Sim	8.00×10^{3}	4.73×10^{2}	0.06	1.000	90.00%	16.00%	1	2.84
	Arnold	NA	Sim	8.00×10^{3}	5.18×10^{2}	0.06	1.000	90.00%	8.00%	1	2.59
	Arnold	NA	Exp	5.00×10^{2}	2.92	0.06	0.120	90.00%	0	1	3.45
2.[124]	VKS	RNG	Sim	NA	1.60×10^{4}	NA	0.200	40.00%	0	1	NA
3.[159]	New	NA	Sim	NA	8.20×10^{1}	1.00	NA	82.00%	0	1	NA
4.[160]	Arnold	Partitioning, Orientation Control and Scaling	Sim	8.55×10^{4}	3.60×10^{4}	1.00	1.000	90.00%	0	1	1.63
	Arnold	Partitioning, Orientation Control and Scaling	Sim	6.57×10^{4}	2.12×10^{4}	1.00	1.000	90.00%	41.00%	1	2.12
	Arnold	Partitioning, Orientation Control and Scaling	Sim	2.00×10^{4}	3.60×10^{4}	16.00	1.000	90.00%	0	1	1.52
	Arnold	Partitioning, Orientation Control and Scaling	Sim	1.49×10^{4}	2.12×10^{4}	16.00	1.000	90.00%	41.00%	1	1.92
5.[162]	Lorenz-Hénon	Partitioning, Orientation Control	Sim	1.88×10^{5}	2.25×10^{3}	1.00	1.000	90.00%	0	1	57.25
6.[163]	Lorenz	Bounded Strategy	Sim	1.60×10^{4}	2.38×10^{1}	NA	NA	95.00%	0	1	NA
7.[166]	Chen	NA	Sim	1.00×10^{4}	0.91	NA	NA	91.25%	0	1	NA
8.[168]	VKS	NA	Sim	1.00×10^{3}	1.60×10^{2}	0.01	1.000	40.00%	0	1	0.53
9.[169]	Lorenz	RNG	Sim	5.91×10^{4}	7.59×10^{2}	NA	NA	84.33%	0	2	NA
10.[170]	Muti-scroll Chua	Flatness Control	Sim	8.00×10^{4}	8.99×10^{3}	0.01	3.000	89.86%	0	1	1.83
11.[171]	Double-scroll	RNG	Exp	NA	NA	NA	NA	NA	0	1	NA
12.[172]	Double-scroll	RNG	Sim	1.50×10^{3}	NA	NA	NA	80.00%	0	1	NA
13.[173]	Modify Hyperjerk	RNG	Sim	3.50×10^{3}	7.50×10^{3}	4.00	1.00	75.00%	0	1	1.36
14.[175]	Logistic Map	Trigonometric Transformations	Sim	1.50×10^{4}	9.90×10^{3}	1.00	1.000	99.00%	0	1	1.04
15.[177]	Logistic Map	PRBG	Sim	4.00×10^{4}	7.70×10^{3}	0.25	1.000	77.00%	0	1	1.88
	Logistic Map	PRBG	Sim	5.00×10^{4}	7.25×10^{3}	0.25	1.000	84.28%	14.00%	1	2.42
16.[180]	Logistic Map	PRBG-Memory Technique	Sim	1.00×10^{4}	7.99×10^{3}	4.00	1.000	79.93%	0	1	1.79
17.[183]	Memristive	NA	Sim	1.10×10^{3}	1.03×10^{1}	0.01	1.000	98.14%	0	1	7.07
18.[184]	Logistic Map	PRBG	Sim	2.00×10^{5}	1.13×10^{5}	NA	NA	90.00%	0	1	NA
19.[185]	Logistic Map	PRBG-Pheromone Model	Sim	3.50×10^{4}	7.82×10^{3}	NA	NA	78.24%	0	1	NA
20.[186]	Logistic Map	PRBG	Exp	NA	0.07	NA	NA	63.33%	0	1	NA
21.[187]	Logistic Map	PRBG	Exp	1.08×10^{3}	0.09	NA	NA	80.00%	0	1	NA
22.[188]	POSCH 7	Partitioning	Sim	1.00×10^{3}	8.74×10^{1}	1.00	0.120	87.37%	0	1	0.95
23.[189]	Chua	Partitioning	Sim	1.00×10^{2}	7.94	1.00	0.120	88.27%	0	1	1.04
24.[192]	Hénon	RNG	Sim	6.00×10^{2}	2.83×10^{2}	0.02	0.090	84.13%	0	1	2.06
	Hénon	RNG	Sim	5.00×10^{1}	2.88×10^{2}	0.02	0.090	85.83%	0	10	1.67
25.[193]	Logistic Map	NA	Sim	7.00×10^{3}	0.97	NA	0.150	96.62%	0	1	NA
26.[194]	Chebyshev	Trigonometric Transformations	Sim	2.00×10^{4}	NA	0.03	0.125	NA	0	1	NA
	Chebyshev	Trigonometric Transformations	Sim	1.00×10^{4}	NA	0.03	0.125	NA	25.00%	1	NA
	Chebyshev	Trigonometric Transformations	Sim	1.89×10^{4}	NA	0.03	0.125	NA	8.00%	1	NA
27.[195]	Chen	Synchronized	Sim	NA	9.00×10^{1}	0.01	1.000	90.00%	0	4	NA
	Chen	Synchronized	Sim	2.00×10^{2}	4.84×10^{1}	0.01	1.000	48.35%	0	4	1.35
	Chen	Synchronized	Sim	2.00×10^{2}	4.92×10^{1}	0.01	1.000	55.89%	12.00%	4	1.29
	Lorenz	Synchronized	Sim	6.94×10^{2}	9.00×10^{1}	0.01	1.000	90.00%	0	4	2.11
	Chen	Synchronized	Sim	6.66×10^{2}	9.00×10^{1}	0.01	1.000	90.00%	12.00%	4	2.30
28.[196]	Arnold	Synchronized	Sim	1.20×10^{3}	8.10	0.01	0.300	90.00%	0	2	6.09
	Arnold	Synchronized	Sim	9.00×10^{2}	6.75	0.01	0.300	90.00%	16.67%	2	5.48
29.[197]	Logistic Map	RNG	Exp	1.20×10^{3}	8.90×10^{1}	0.09	1.000	89.90%	0	1	2.77
30.[198]	Chua	Partitioning	Exp	1.00×10^{3}	7.98	NA	NA	88.72%	0	1	NA
31.[199]	Lorenz, Hamilton, Hyper	Synchronized	Exp	NA	NA	NA	1.000	NA	0	1	NA

以上就是2023年出版的几篇比较典型的自动驾驶运动规划技术领域相关的综述. 后续会持续补充.