

Towards Autonomous Driving with Small-Scale Cars: A Survey of Recent Development

Dianzhao Li, Paul Auerbach, and Ostap Okhrin

Abstract—While engaging with the unfolding revolution in autonomous driving, a challenge presents itself, how can we effectively raise awareness within society about this transformative trend? While full-scale autonomous driving vehicles often come with a hefty price tag, the emergence of small-scale car platforms offers a compelling alternative. These platforms not only serve as valuable educational tools for the broader public and young generations but also function as robust research platforms, contributing significantly to the ongoing advancements in autonomous driving technology. This survey outlines various small-scale car platforms, categorizing them and detailing the research advancements accomplished through their usage. The conclusion provides proposals for promising future directions in the field.

Index Terms—Small-scale car, autonomous vehicles, robotics

I. INTRODUCTION

OVER the past few decades, extensive research on autonomous driving (AD) has been conducted by both academic communities and industry stakeholders. However, the fruition of fully functional applications for AD systems is anticipated to materialize in the coming decades. The question arises: *Can we proactively prepare our society for the oncoming fully autonomous driving?* Despite assertions from researchers that autonomous vehicles (AVs) will mitigate human error and enhance safety compared to human drivers, public apprehensions persist regarding the ethical and safety dimensions of AVs [1], [2]. Encouragingly, individuals with prior experience with AVs and younger generations exhibit a more optimistic stance toward these technologies [3]. Hence, the affirmative response to this question is clear. Given that those who will design autonomous systems are currently in high school, and those who will coexist with AVs are presently in elementary schools, the optimal preparation involves providing opportunities for the public to have touch with AD systems now. To this end, a small-scale car platform emerges as an ideal choice, serving not only educational purposes but also facilitating researchers in testing their autonomous systems on a tangible platform.

Undoubtedly, research in AD research for full-scale cars holds promise. However, to provide the public and research communities with a more cost-effective and accessible avenue to engage with AD, the replication of small-scale car platforms

stands out. In educational settings, small-scale cars prove to be an excellent choice for schools, especially with STEM focus, offering students their initial exposure and hands-on experience with AD while simultaneously fostering increased public awareness. On the research front, the availability of such research platforms lowers entry barriers, inviting a broader spectrum of researchers into AD exploration. This, in turn, propels advancements in AD and establishes a virtuous circle of continuous improvement and innovation before their integration into full-scale autonomous vehicles. As evidenced in Fig. 1(A), the quantity of research papers focused on small-scale car platforms has experienced a substantial surge in the past two decades. Following a relatively gradual incline before 2016, this field has undergone a notable expansion, particularly catalyzed by the introduction of a series of well-known platforms. Hence, to advance ongoing research initiatives and enhance public awareness, we attempt to comprehensively survey the existing small-scale platforms for educational and research purposes. We also aim to benchmark the AD tasks accomplished by these platforms. To the best of our knowledge, this survey represents the first of its kind to undertake such an extensive analysis.

The rest of this paper is organized as follows: In the second section, we examine commonly employed small-scale car platforms, accompanied by insights into their simulators. The third section provides a comprehensive overview of the AD tasks accomplished within the research community. Following that, the fourth section inspects the sensor setups employed in these platforms. The subsequent section outlines promising directions for future developments, and we draw our conclusions in the sixth section.

II. PLATFORMS

For full-scale cars, the standardized dynamics and sizes are mandated by road regulations. In contrast, smaller-scale cars, designed without regulatory constraints, are crafted for diverse research purposes by various groups of researchers and enthusiasts. Recognizing these disparities, this survey establishes a clear definition for AD robot cars, setting them apart from other autonomous robots. In this context, an AD small-scale car platform refers to a miniature vehicle equipped with technologies enabling autonomous operation. This includes sensors, processing units, control actuators, and often a set of predefined tasks or challenges for testing and development. In terms of size, namely the scale factors, there is considerable variability among different platforms. Platforms intended to carry a lot of sensors and for outdoor operation can reach

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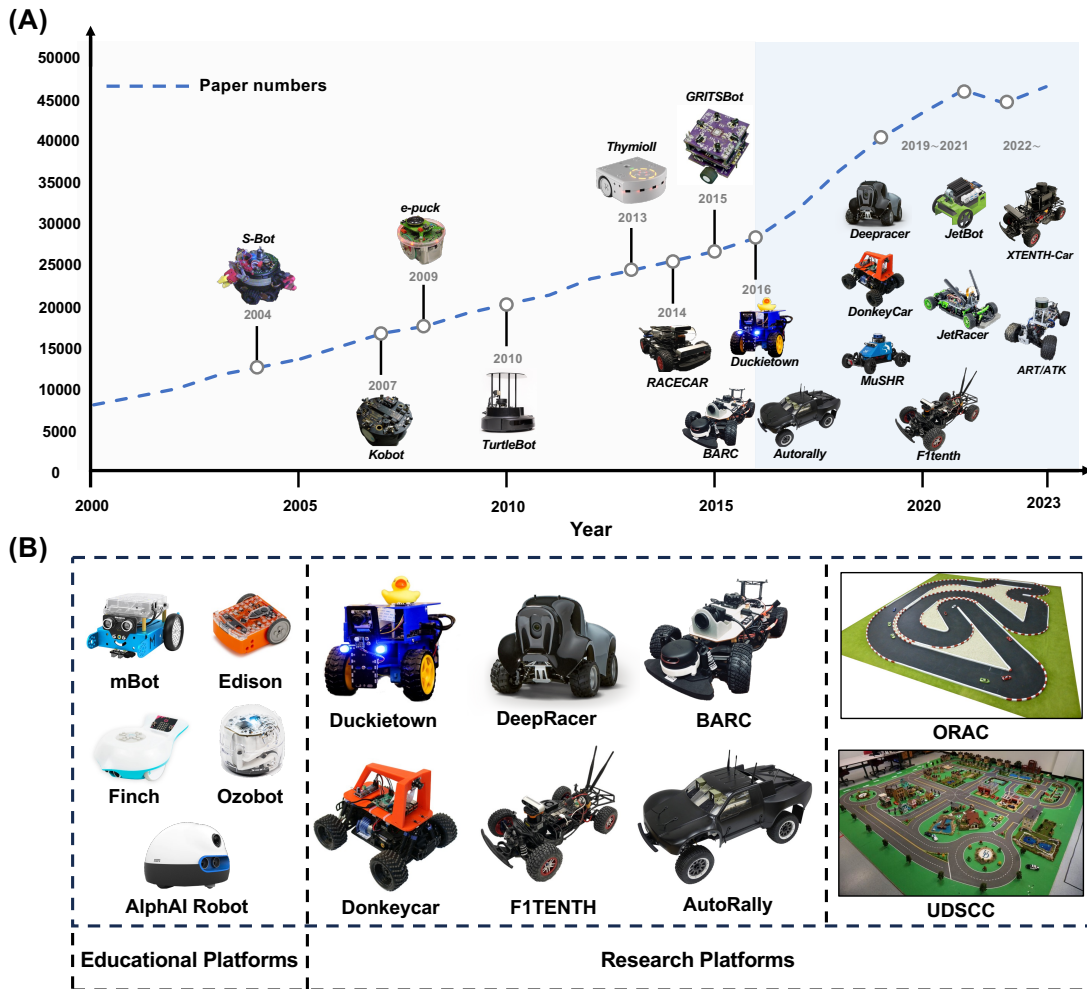


Fig. 1. Illustration of the development and current states of small-scale car platforms, each depicted platform image sourced from its respective paper or website. (A) Based on published studies each year on Google Scholar with the search terms: robot car, the research on small-scale cars has seen substantial growth in the number of papers over the years. In the early 2000s, projects like s-bot [4], e-puck [5], and TurtleBot [6] emerged. Starting around 2016, with the introduction of Duckietown [7], BARC [8], and Autorally [9], there was a significant increase in research papers. This trend continued with the development of projects like DeepRacer [10], Donkeycar [11], and F1TENTH [12]. More computationally advanced small-scale cars have been introduced in recent years, such as ART/ATK [13] and XTENTH-CAR [14]. (B) Examples of small-scale car platforms, categorized into educational platforms and research platforms, including multiple vehicle setups such as ORAC [15] and UDSSC [16].

almost 1 meter in length [9]. On the other end of the spectrum, platforms developed for investigating swarm dynamics are notably compact, with some as small as 3.3x3.3cm [17]. The most common form factor is the 1/10th scale, representing a model approximately one-tenth the size of a full-scale car. This scale is frequently employed in hobby Remote-Control (RC) vehicles, forming the foundation for numerous platforms [8], [11], [12], [14], [18]–[24]. Regarding the dynamic system, full-size cars commonly use Ackermann steering mechanics, rotating the front axle to facilitate left or right turns [25]. However, due to the mechanical complexity of this system and its limitations in certain situations, small-scale car platforms initially favored the use of a differential steering system. In this system, the left and right sets of wheels are driven independently, enabling turns by driving one set of wheels faster than the other. Nevertheless, as illustrated in Fig. 1, recent advancements in this field have seen the increased adoption of the more realistic Ackermann steering system in

small-scale car platforms.

A. Hardware platforms

Before we introduce the different platforms, we categorize small-scale car platforms into distinct groups based on their target users and complexity. First are the educational platforms often powered by MicroBit or Raspberry Pi, predominantly accessible in the commercial market, including Makeblock mBot [26], Edison [27], AlphaI Robot [28], TinkerGen MARK [29], and Robolink Zumi [30], typically using platform-specified block and visual programming languages. These platforms are carefully crafted to engage students ranging from early childhood to elementary school and even graduate programs in the interactive exploration of autonomous cars. They offer users comprehensive tools, enabling them to effortlessly construct and program robot cars capable of executing diverse tasks. With these platforms, students can readily accomplish basic tasks like simple lane following and obstacle avoidance.

The subsequent tier has a more sophisticated system, affording users enhanced opportunities to innovate and develop new functionalities within the platform. The typical platforms are e-puck [5], Pheeno [31], Thymio [32], MarXbot [33], Turtlebot [6], and Duckietown [7]. The e-puck, Pheeno, Thymio, and MarXbot are commonly employed in swarm robot research due to their compact sizes. The Duckietown ecosystem, originating in 2016 at MIT, serves as an educational tool for instructing students in the realms of autonomous and connected driving. Comprising cost-effective vehicles known as Duckiebots, each unit is outfitted with either a Raspberry Pi or a Jetson Nano as its computing unit. Sensor-wise, the Duckiebots employ an RGB Raspberry Pi camera, an inertial measurement unit (IMU), wheel encoders, and a front-facing distance sensor. The platform also facilitates the incorporation of a central localization system through "watchtowers." Propelled by two DC motors on each of the two driven wheels, the cars adhere to a differential drive pattern. Duckietown is commercially available and has proven effective in various applications, with lane-keeping using the RGB camera being the most common [34], [35]. Additionally, it has been employed for tasks such as obstacle and traffic sign detection [36], [37]. Another commercially available platform is the AWS DeepRacer [10] by Amazon Web Services. This platform also relies on an RGB camera for sensory input, supplemented by an upgrade kit featuring a second camera and a LiDAR sensor. The execution of learned strategies is managed by a small compute board equipped with an Intel Atom CPU. With Ackermann steering implementation, DeepRacer is also primarily used for tasks like lane-keeping [38], [39] and obstacle avoidance [40], [41].

For users seeking open-source platforms and aiming to construct a platform from the ground up, two common options are Donkeycar [11] and F1TENTH [12]. Donkeycar, a collaborative effort within a community, provides comprehensive instructions for constructing the platform. Due to its open-source nature, individual cars can vary significantly, accommodating diverse sensor configurations. The foundational platform centers around a 1/10th scale RC car, featuring Ackermann steering, and is customized with a Raspberry Pi or Jetson Nano as the compute unit, along with a Raspberry Pi camera serving as its primary sensor. Users have the flexibility to incorporate additional sensors such as IMUs and encoders, and there are options for integrating LiDAR into the system. Given its open-source framework, users can extend the platform's functionality according to their needs. Originally designed for autonomous racing, Donkeycar is also commonly applied for tasks like lane-keeping [42], [43] and obstacle avoidance [44]. Likewise, F1TENTH is built upon a 1/10th scale RC car platform featuring Ackermann steering. Its compute unit is a Nvidia Jetson, complemented by a 2D LiDAR serving as the primary sensor. Additional features include an IMU and odometry information provided by the VESC motor controller¹, with an option to integrate an extra RGB camera. With its high-speed capable base platform, F1TENTH is primarily utilized for autonomous racing tasks [45], [46], while, it also finds application in fundamental tasks such as lane-keeping

[47] and obstacle avoidance [48], [49].

For outdoor applications, the Autorally [9] platform takes center stage, incorporating an off-the-shelf RC car platform. In comparison to the Donkeycar and F1TENTH platforms, Autorally is larger, utilizing a 1/5th scale model car. Leveraging this increased size, it incorporates a more powerful compute unit consisting of a consumer computer mainboard with an Intel i7 CPU. The primary sensors include two industrial synchronized RGB cameras for obtaining stereo images, an IMU, magnetic encoders for odometry measurement, and a GPS receiver. Due to its substantial size and high-performance components, Autorally is mainly employed for racing tasks [50]–[52]. The platform offers a variety of sensor combinations for racing approaches, with many leveraging the combination of GPS and IMU data [53], [54], as well as those that integrate camera and IMU data [55], [56].

The significance of a small-scale smart city platform, accommodating multiple vehicles, is underscored as it plays a crucial role in achieving harmony and efficient collaboration of a fully autonomous driving world. To this end, the University of Delaware Smart Scaled City (UDSSC) [16], developed for education and research on connected and autonomous driving, emerges as a distinctive contribution. It features a downscaled city environment with diverse traffic scenarios, including intersections and roundabouts, and incorporates Micro Connected and Automated Vehicles (MCAV). Built on the Pololu Zumo² platform, the MCAVs have a differential drive DC motor setup with encoders, an IMU, and an Arduino³. Each vehicle is additionally equipped with a Raspberry Pi as its compute unit, a line-following sensor, and a front-facing distance sensor. Notably, the absence of a camera or LiDAR prompts the utilization of a central localization system for accurate positioning. UDSSC serves a specialized purpose, exclusively engaging in cooperative and connected driving tasks such as merging [16] and roundabout traversal [57]–[59]. The platform is unfortunately not accompanied by any open-source code or hardware accessibility and is not available for purchase.

For the sake of brevity, we have condensed the details of the usually used platforms into Table I. This table offers a comparative analysis, outlining key characteristics such as steering dynamics, installed sensors, utilized software frameworks, and, when relevant, the simulation software integrated into each platform.

B. Simulators

Before employing the autonomous system in real platforms, a simulation is often used first to test the performance. For small-scale cars, numerous simulators exist to facilitate the training, testing, and evaluation of autonomous systems.

First, for the requirements of simulating the vehicle dynamics and control systems, CarMaker [75] and CarSim [76] emerge as notable choices. They furnish simulation environments capable of comprehensively assessing various facets

¹<https://vesc-project.com/>

²<https://www.pololu.com/category/170/zumo-32u4-oled-robot/>

³<https://www.arduino.cc/>

TABLE I
SMALL-SCALE CAR PLATFORMS: AN OVERVIEW OF THE HARDWARE AND SOFTWARE SETUP.

Platforms	Size	Vehicle Dynamics	Sensors	Computation Unit	Software Framework	Simulation Platform	Open-source ¹	Commercial
AutoRally [9]	1/5th	Ackermann	Camera, IMU, GPS, Hall-effect sensor	Intel i7-6700 Nvidia GTX-750ti SC	ROS	Gazebo	SW	No ²
ART/ATK [13]	1/6th	Ackermann	Camera, 3D LiDAR	Jetson Xavier NX	ROS2	Chrono	–	No
BARC [8]	1/10th	Ackermann	Camera, LiDAR, IMU, GPS	ODROID-XU4	ROS	–	–	No
Donkeycar [11]	1/10th 1/16th	Ackermann	Camera, LiDAR, IMU, Encoder	RPi/Jetson Nano	Python	Donkeycar Gym	SW, HW	No ²
FITENTH [12]	1/10th	Ackermann	Camera, LiDAR, IMU	Jetson TX2	ROS	Gazebo FITENTH Gym	SW	No ²
RACECAR/MIT [18]	1/10th	Ackermann	Camera, LiDAR, IMU, Encoder	Jetson Tegra X1	ROS	Gazebo	SW, HW	No ²
MuSHR [19]	1/10th	Ackermann	Camera, LiDAR, IMU, Bump sensor	Jetson Nano	ROS	–	SW	No ²
Qcar [20]	1/10th	Ackermann	Camera, LiDAR, IMU, Encoder, Microphone	Jetson TX2	ROS, Python, MATLAB	Gazebo	SW	✓
Autominy [23]	1/10th	Ackermann	Camera, LiDAR, IMU, Encoder	Intel NUC	ROS	Gazebo	SW	No
JetRacer [22]	1/10th 1/18th	Ackermann	Camera	Jetson Nano	–	–	SW, HW	✓
Autonomouscar [21]	1/10th	Ackermann	Camera, LiDAR, IMU, Encoder, ToF Sensor, Indoor GPS	RPi 4	ROS, LabVIEW	–	SW, HW	No
CoRoLa [24]	1/10th	Ackermann	Camera, Encoder, Ultrasonic sensor	RPi 4	ROS2	Based on LGSVL	–	No
AutoDRIVE [60]	1/14th	Ackermann	Camera, LiDAR, IMU, Encoder, Indoor GPS	Jetson Nano	ROS	AutoDRIVE Simulator	SW, HW	No
PiRacer [61]	1/16th	Ackermann	Camera	RPi 4	ROS	–	–	✓
Duckietown [7]	34x15x23cm	Differential	Camera, IMU, Ultrasonic sensor	RPi 2/Jetson Nano	ROS	Gazebo Duckietown Gym	SW	✓
DeepRacer [10]	1/18th	Ackermann	Camera, LiDAR, IMU	Intel Atom	ROS	Gazebo	SW	✓
ITS car [62]	1/18th	Ackermann	Camera	RPi 3 B+	–	–	–	No
μcar [63]	1/18th	Ackermann	IMU, Encoder	RPi Zero W	–	–	SW, HW	No
UDSSC MCAV [16]	1/25th	Differential	IMU, line following, IR sensor	RPi 3	ROS	SUMO	–	No
Chronos [64]	1/28th	Ackermann	IMU, Encoder	Espressif ESP32	ROS	–	SW, HW	No
Go-CHART [65]	1/28th	Differential	Camera, LiDAR, Bump sensor	RPi 3	ROS	–	SW, HW	No
Cambridge MiniCar [66]	75x81x197mm	Ackermann	Indoor positioning system ³	RPi Zero	–	–	SW, HW	No
ORCA Racer [15]	1/43th	Ackermann	IMU, Indoor positioning system ³	ARM Cortex M4	IMU	–	–	No
Epuck [5]	70mm ∅	Differential	Camera, IMU, IR sensor, Speaker, Microphone	STM32F407	ROS	Enki, Webots	–	✓
Turtlebot [6]	34x34x35cm	Differential	Camera, LiDAR, IR sensor	RPi 4	ROS	Gazebo	SW	✓
Kilobot [17]	33mm ∅	Vibration	IR sensor	Atmega 328	–	–	–	✓
GRITSBot [67]	31x30mm	Differential	IMU, IR sensor	Atmega 328	–	–	SW, HW	No
HydraOne [68]	27x32cm	Omni	Camera, 3D LiDAR, Encoders	Jetson TX2	ROS	–	HW	No
Pheno [31]	10cm ∅	Differential	Camera, IMU, Encoder, IR sensor	ATmega328P ARM Cortex-A7	Python	–	–	No
Thymio [32]	11x11cm	Differential	IR sensor, Accelerometer, Microphone, Thermistor	PIC24F	ROS, VPL	Gazebo	–	✓
MarXbot [33]	17cm ∅	Differential	Camera, IMU, IR sensor, 2D force sensor	ARM 11 processor	ROS	Gazebo	–	No
WolfBot [69]	17.5cm ∅	Omni	Camera, IMU, IR sensor, Microphone	BeagleBone	ROS	MATLAB	SW, HW	No
LabRAT [70]	–	Differential	IR sensor	Atmega324p	C	Player/Stage	SW, HW	No
mAGV [71]	–	Differential	IMU, Encoder, RFID	RPi Zero W	ROS	–	–	No
Rover [72]	–	Differential	Camera, LiDAR, IMU, GPS, Ultrasonic sensor	Jetson TK1	ROS	Gazebo	–	No
Jetbot [73]	–	Differential	Camera, IMU	Jetson Nano	ROS	Gazebo	SW, HW	✓
Makeblock mBot ⁴ [26]	–	Differential	Ultrasonic Sensor, IR sensor, Line tracking sensor	Arduino	mBlock ⁵	–	–	✓
Edison ⁴ [27]	80x80x40mm	Differential	IR sensor, Line tracking sensor	–	EdBlock, EdPy ⁵	–	–	✓
Alpha1 Robot ⁴ [28]	–	Differential	Camera, Ultrasonic Sensor, Line tracking sensor	Raspberry Pi Zero	Python	–	–	✓
Ozobot Evo ⁴ [74]	32mm ∅	Differential	IR sensor, Speaker	–	OzoBlockly ⁵	–	–	✓
Finch Robot ⁴ [74]	–	Differential	Encoder, Ultrasonic sensor, Line tracking sensor, IR sensor, Speaker	MicroBit	Python	–	–	✓
TinkerGen MARK ⁴ [29]	200x185x92mm	Differential	Camera, Ultrasonic Sensor	Arduino	MicroPython	–	–	✓
Robolink Zumi ⁴ [30]	95x67x70mm	Differential	Camera, IR sensor	RPi zero	Python, Blockly ⁵	–	–	✓

¹ For open-source types, SW: Software and HW: Hardware.

² Build guides with off-the-shelf parts are provided.

³ Motion Capture Systems.

⁴ Educational robot kit.

⁵ Platform-specified block and visual programming languages.

of vehicle behavior, encompassing handling, braking, and acceleration, across diverse driving conditions. For autonomous driving systems, the sensor models are as important as the physics engine, therefore, Gazebo [77] plays an important role in robotics and related research areas. It provides a modular system that facilitates the integration of diverse sensors and physics models. For small-scale cars such as Turtlebot, Duckietown, DeepRacer, FITENTH, MuSHR, Autorally, and others, simulations based on Gazebo have been developed. For a macro-scale simulation, SUMO [78] emerges as a platform for in-depth analysis and optimization of transportation systems, road networks, and traffic management strategies. Similarly, Highway-env [79] provides a gym-based environment specifically designed for simulating highway-based road topologies. In the realm of more detailed autonomous driving setups, various open-source simulators have gained popularity, with

TORCS [80], CARLA [81], AIRSIM [82], DeepDrive [83], and LGSVL [84] being notable examples. These simulators not only boast high-fidelity physics engines for simulating vehicle dynamics but also support a diverse array of sensors. This allows for hyper-realistic simulations of traffic environments, facilitating rigorous testing of AVs. For multi-agent systems, MADRaS [85], built on top of TORCS, and Flow [86], built on top of SUMO, are commonly used.

Besides the universal simulators, some simulators are specially tailored for small-scale cars. For example, Gym-Duckietown [87] for Duckietown, provides a fast, open, and highly customizable simulator, to train or test various algorithms for different driving tasks. The DeepRacer cloud simulator from Amazon for the DeepRacer racing platform provides an online platform to customize the algorithm, choose the tasks, and modify the structure of the networks. Donkey-

Gym [88] for Donkeycar is similar to Gym-Duckietown, but built on the Unity game platform with internal physics and graphics, also the F1TENTH Gym environment [89] for the F1TENTH platform. With these specially designed simulation platforms, the real-world deployment of autonomous small-scale cars will be facilitated after training and testing in the simulation. Nevertheless, the Simulation to Reality (Sim2Real) gap remains a challenge that needs to be addressed before successfully deploying the trained algorithms in the real world.

C. Sim2Real transfer

Sim2Real is a concept in robotics and AVs that involves transferring skills, knowledge, or models acquired in a simulated environment to real-world applications. Here, the real-world setting or scenario in which the robot is intended to operate and execute tasks is termed the target domain. Conversely, the data, and experiences, shaping the development of the robotic system are called the source domain. The core objective of Sim2Real is to devise algorithms and methodologies capable of effectively bridging the disparities between these two domains, known as the *Sim2Real gap*. For instance, this gap may manifest as dynamic differences or discrepancies in the sensing part, where the simulated images and the real images are different. Although the Sim2Real transfer is primarily centered on transferring Deep Reinforcement Learning (DRL) policies from simulation to the real world, it can also be more broadly considered as Machine Learning (ML) problems for the sensing part, for the agent facing situations in the real world that have not appeared in simulation. To address the Sim2Real gap, an array of methods is proposed, including system modeling, dynamics randomization, and randomization for sensing. Here we introduce the most used methods for small-scale cars.

The first approach for the real-world application of small-scale cars is *Zero-shot Transfer*, where the trained model is directly applied in real-world settings. For this, the Imitation Learning (IL) approach is usually involved with the dataset collected in the real-world platform. The agent is trained to mimic the behavior of the expert [9], [34], [55], [56], [65], [90]–[92]. In addition to IL, *Zero-shot Transfer* for DRL can be achieved with compact observation and output space [93]–[95]. Another noteworthy approach is *Transfer Learning*, which aims to improve the performance of the target agent in the target domain by transferring the knowledge contained in different but related source domains [96], for example, for Sim2Real transfer, the process typically includes initially pre-training a model in a simulated environment and subsequently fine-tuning it using real-world data. When the labeled data in the target domain is scarce or expensive to obtain, *Domain Adaptation* is used. As a subset of transfer learning, it seeks specifically to minimize the distribution mismatch between the source and target domains, allowing the model to generalize better across different domains. Another frequently used approach is *Domain Randomization*, in which the randomness and variation are introduced during simulation to make the model more robust to different real-world conditions [97]. It works by for example randomly varying

simulation parameters, such as lighting conditions, textures, object appearances, and physics properties during training. For small-scale car platforms, Duckietown and DeepRacer provide *Domain Randomization* option in the simulation, which is easier for the users to tackle Sim2Real issue [10], [38], [98], [99].

III. BENCHMARK TASKS

Autonomous driving systems for normal and small-scale vehicles are normally categorized into two distinct pipelines: the *end-to-end system* pipeline and the *modular system* pipeline. As illustrated in Fig. 2, a modular system comprises multiple subsystems that perform various tasks such as perception and localization, mapping, path planning, and control [100], [101]. Each subsystem focuses on specific functionalities and tasks. First is the perception system, where sensors such as cameras and LiDAR are used to gather information about the surroundings, including lane markings, obstacles, traffic signs, and other vehicles. Following this, the localization and mapping system leverages GPS, odometry, IMU, or techniques like simultaneous localization and mapping (SLAM) to precisely pinpoint the position within the environment while concurrently creating a detailed map of its surroundings. The perception system creates an intermediate representation of the environment for subsequent utilization.

The representation module then uses the information from the perception module and further processes the sensor data with sensor fusion techniques or creates an object map with the predicted state of each object within the sensor range. The combination of the perception module and the representation module can be seen as the scene understanding, which provides an abstract high-level representation of the environment [101]. Afterward, the planning system maps out a safe and efficient route to reach the destination. Normally, in the autonomous driving system, the planning phase is divided into two different parts, namely *global path planning* and *local path planning* [102]. Global path planning refers to the process of determining an optimal or feasible route from the current position to its destination and is done considering the entire environment and involves high-level decision-making. Local path planning or path following, on the other hand, focuses on the immediate surroundings of the vehicle and deals with making real-time adjustments to adhere to the planned global path. Finally, the control module generates driving commands based on the processed information. In control theory, the primary goal is to minimize a cost function. Various methodologies are employed for the control system, classical controllers such as the Proportional–Integral–Derivative (PID) controller, Model Predictive Control (MPC), and ML-based controllers such as IL or DRL.

An end-to-end system, on the other hand, is characterized by a unified architecture that aims to learn the entire mapping directly from raw sensor inputs to driving actions without explicitly decomposing the task into separate modules [103]–[105]. It involves training a comprehensive learning model with ML methods, IL or DRL, directly process raw sensor data and output control commands. End-to-end systems potentially

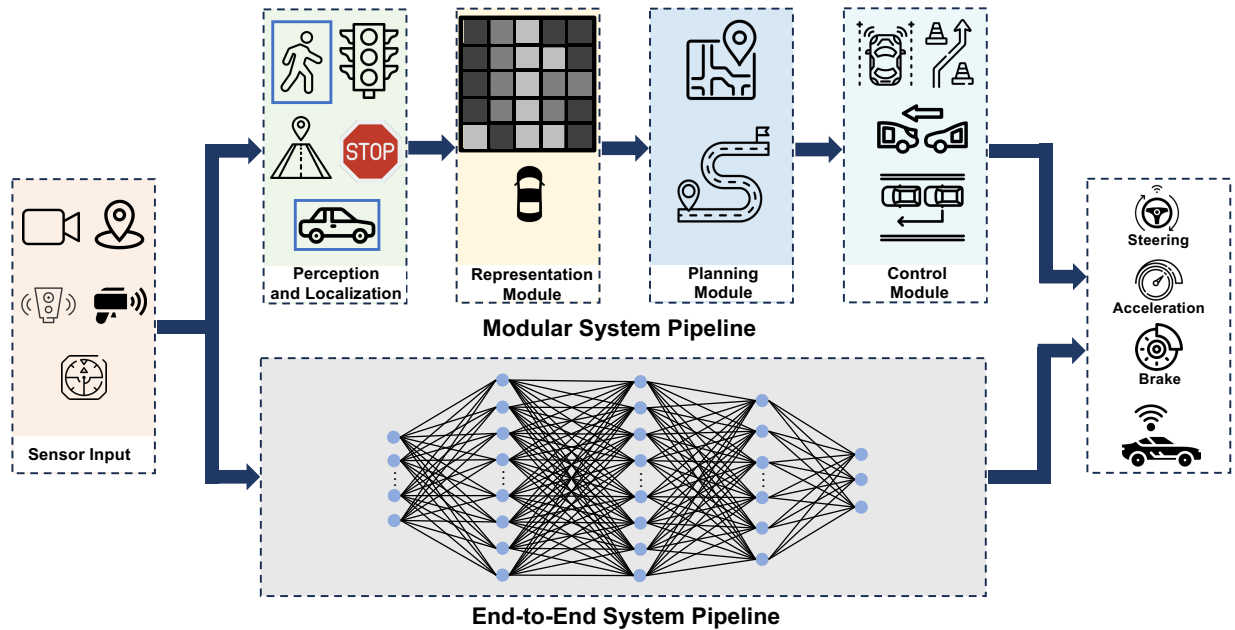


Fig. 2. Comparison of two pipelines for the autonomous driving system. An end-to-end system maps raw sensor inputs directly into control commands, whereas a modular system includes multiple subsystems to process the sensor inputs sequentially and output control commands.

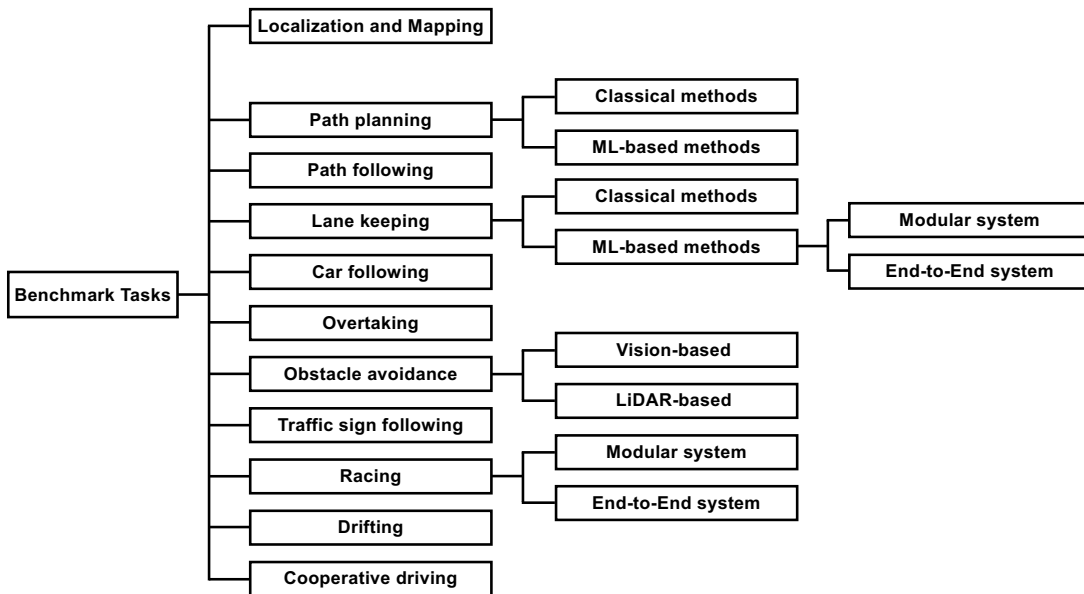


Fig. 3. Research in the literature concerning small-scale cars is classified into various benchmark tasks in this survey, ranging from localization and mapping, path planning and following, lane keeping to racing, and cooperative driving.

simplify the system architecture by eliminating the need for handcrafted modules and feature engineering.

In this section, our focus is directed toward discussing various tasks studied in the literature and the methods developed to handle these tasks using modular or end-to-end systems. The detailed methodologies for achieving these tasks will not be discussed, instead, we will refer to the respective papers. The benchmark tasks categorized in this survey are illustrated in Fig. 3.

A. Localization and Mapping

The localization and mapping, which, although commonly viewed as a subsystem within the modular autonomous system, are also regarded as distinct and extensively researched topics in the literature.

GPS can directly provide the location of the vehicle, but the accuracy is affected by a list of factors, such as atmospheric conditions, satellite geometry, signal blockage (buildings, trees, etc.), multipath interference, and the quality of the GPS receiver. Differential GPS (DGPS) systems and augmentation techniques can be used to enhance GPS accuracy

by correcting some of these error sources, but cannot fulfill the accuracy which is extremely important when it is small-scale cars. Typically, an IMU consists of various sensors, such as accelerometers and gyroscopes to measure and report acceleration and angular velocity in three dimensions: pitch, roll, and yaw with high rates. However, errors such as sensor drift and integration errors can accumulate over time with IMU, leading to inaccuracies in long-term measurements. To address the issues, the two sensors are often integrated through sensor fusion methods, such as Kalman filter (KF) [106] or its variations as extended Kalman filter (EKF) or unscented Kalman filter (UKF) [107], to enhance accuracy and reliability in determining the position and orientation. As in the studies by [108]–[110], that use BARC small-scale cars, KF makes the fusion of IMU, wheel encoders, and indoor GPS measurements to achieve an accurate localization. In recent research, [111] presents an approach to use KF to fuse multiple-camera images with the AprilTag system and wheel odometry. The results are validated with the OptiTrack Motion Capture System (MoCap). OptiTrack system can also be used as a global localization system and provide high accuracy pose estimation but with higher cost [112], more detail will be discussed in Section IV-E.

For small-scale vehicles, the primary sensor for localization and mapping components utilized is the LiDAR. They collaborate with a pre-defined map or SLAM technology to navigate and position the vehicle effectively within its environment [113]. A well-established method for localizing robot cars with LiDAR sensors on the pre-defined map involves the use of a particle filter (PF) as explored in [45] with F1TENTH. However, the computational demands of the PF present challenges, especially for computation resources and space-constrained small-scale robot cars. To enhance performance, [114] introduces the Compressed Directional Distance Transform (CDDT) on the RACECAR platform. This method focuses on expediting ray casting within 2D occupancy grid maps and accelerating sensor model computations to mitigate computational expenses. While comprehensive survey papers delve into various SLAM techniques [115]–[118], encompassing feature-based, LiDAR-based, visual, and graph SLAM, this study offers a concise overview of three prevalent SLAM methods employed with small-scale cars: GMapping [119]–[121], HectorSLAM [72], [122]–[125], and Cartographer [126]–[128].

GMapping, utilizing a particle filter-based approach, stands as one of the most widely used SLAM algorithms, adept at handling non-linear sensors and non-Gaussian noise [129]. To address computational expenses inherent in particle filters, the Rao-Blackwellized Particle Filters (RBPF) algorithm is introduced to combine odometry with scan-matching techniques. Based on particles representing a sampling from a multimodal map proposal distribution, this approach effectively closes loops without necessitating additional methods. The efficacy of GMapping hinges on both 2D LiDAR data and odometer information, utilizing the latter significantly to curtail the number of particles involved in the mapping process. In contrast, HectorSLAM exclusively depends on LiDAR sensors and leverages the high sampling frequency

of modern 2D LiDAR [130]. It swiftly provides a 2D pose estimate at the scan rate utilizing a scan-matching algorithm [130]. Upon receiving raw LiDAR data and joint values, HectorSLAM undergoes preprocessing before importing the data to the scan matching module, applying the Gauss-Newton approach [131] to estimate the optimal pose. As robots traverse longer trajectories and handle substantial data volumes, the limitations of particle-based approaches become evident. Graph optimization algorithms emerge as more reliable and efficient solutions for managing these large-scale datasets. As a typical Graph SLAM, the Cartographer takes odometry data as an initial estimate for the local optimizer [132]. This optimizer focuses on determining the most probable relative pose between the scan and local submap coordinate frames. These relative poses serve as constraints for a Sparse Pose Adjustment optimizer, specifically engineered to address loop closure challenges. Cartographer operates as a dual-pronged approach to the SLAM problem, comprising the front-end (Local SLAM) and back-end (Global SLAM). The front-end executes critical tasks like scan matching for loop closure detection and estimating the pose. Conversely, the back-end optimizes poses regularly by forming a graph to minimize loop-closing constraints, thereby minimizing successive pose errors.

Moreover, a compelling approach gaining traction involves leveraging ML methods to address mapping and localization challenges. One notable instance is the GALNet proposed in [133] implemented on the Autonomy platform. GALNet employs a Deep Neural Network (DNN), utilizing two timestamps of inertial, kinematic, and wheel velocity data to estimate poses effectively. With the success of Transformer architecture in various research fields, [134] introduces the Perception-Action Causal Transformer (PACT) architecture. This model constructs a representation from sensor data by autonomously predicting states and actions over time, laying the groundwork for subsequent task-specific networks for localization and mapping. Pre-trained models are employed initially and later fine-tuned for specific tasks, demonstrating validation on MuSHR with LiDAR sensor data. For image-based localization, [135] proposes an effective framework leveraging a pre-trained local feature transformer (LoFTR). This framework employs a constrained 3D projective transformation between consecutive key images to establish a visual map on Jetbot. These studies underscore the growing interest and potential of ML methodologies, including neural networks and transformer architectures, in revolutionizing mapping and localization paradigms by offering robust, data-driven solutions that outperform traditional approaches.

B. Path planning and following

Similar to localization and mapping, path planning and path following can be regarded as distinct tasks for small-scale cars. While often studied together, both are essential components that are merged to form a cohesive navigation process within autonomous systems.

1) *Path planning*: Path planning in autonomous driving refers to the process by which a self-driving vehicle determines

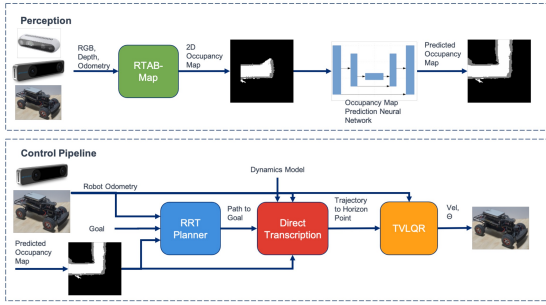


Fig. 4. Overall perception and control pipeline in [147]. The perception module receives onboard sensor data and produces a predicted occupancy map using a U-Net style generative neural network. The control algorithm receives the robot state, predicted occupancy map, and goal point and generates collision-free trajectories with RRT.

a safe and efficient route from its current location to a desired destination while navigating through its environment [136]. This task involves creating a trajectory or path that the vehicle can follow, considering various factors such as obstacles, road conditions, and traffic regulations, and aims to ensure safe and reliable navigation while optimizing factors like travel time, and energy efficiency. Path planning algorithms vary in complexity and we specify them into traditional [137]–[139] and ML-based techniques [140], [141].

a) Traditional methods: The most traditional method is Dijkstra’s algorithm [137], which is used in [142] for path planning with SLAM methods to obtain the global map information. Among many applications of the A* [138], [40] uses the A* algorithm to obtain optimal paths for a racing car, and [143] integrates the Hybrid A* algorithm [144] with a learned model utilizing a cost function. This integration aimed to tackle unforeseen obstacles encountered during navigation, which often escape the detection of traditional global path planning algorithms. In the work by [145] and [146], genetic algorithms (GA) are investigated to generate a global path for a mobile robot in the grid-based environment. Furthermore, to extend the planning capabilities beyond the sensor horizon, [147] utilizes a generative neural network trained on real-world data to predict occupancy maps beyond sensor limitations, see Fig. 4. This predictive capability assists in facilitating planning processes. Authors leverage the Rapidly-Exploring Random Tree (RRT) algorithm [139] to generate a global path, followed by a local planner that orchestrates trajectories until the end of the predicted map.

b) ML-based methods: Path planning, treated as an optimization problem, has also seen the successful application of various ML methods, resulting in notably high-performance outcomes. For instance, [148] uses Q-Learning, a classical RL algorithm, to generate a global path for robots, which achieves a shorter and smoother path compared with the RRT algorithm. A framework is introduced in [149] comprising a mapper, global policy, and local policy for image-based navigation for Jetbot. The mapper undergoes supervised learning using camera images to generate an occupancy grid map. Subsequently, a global policy employing DRL techniques takes both the map and the position as input to determine the long-term goal. Following this, a planner, employing the A* algorithm,

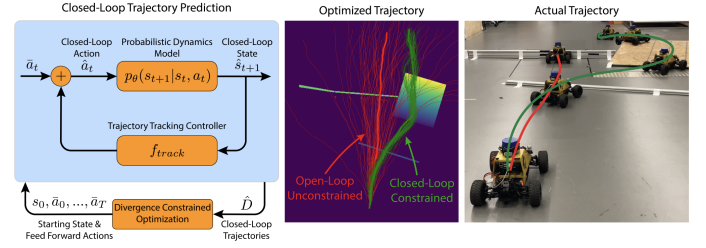


Fig. 5. An overview of the method in [150]. The probabilistic dynamics model is trained using a multistep loss that considers how uncertainty propagates. The trajectory tracking controller is used to predict a distribution of closed-loop trajectories. The divergence constrained optimizer is used to find a closed-loop trajectory with low divergence for MuSHR cars.

computes the short-term goal, which is then forwarded to the local planner for further execution.

Even with prior maps and acquired information, managing uncertainty during planning and driving remains a significant challenge. To address these uncertainties, [150] introduces a model-based RL algorithm incorporating a probabilistic dynamic model. This method aims to mitigate uncertainty during planning stages and prevent shortsighted decisions, illustrated in Fig. 5. In the related approach, [151] uses Bayesian Residual Policy Optimization (BRPO) with an ensemble of expert policies. Authors train the policy ensemble with BRPO to diminish overall system uncertainty, enabling safe navigation within partially observable environments. Demonstrated on the MuSHR platform, proposed framework integrates a global localization system, ensuring destination-reaching capabilities while avoiding collisions with other moving vehicles.

2) Path following: Once the path is established, the path following becomes the subsequent step, encompassing the capability of the vehicle to precisely track the designated path in real time. Here, the control system interprets the planned trajectory and orchestrates the essential actions required for the vehicle to adhere to the intended path. Path following necessitates a continual adjustment of the movements based on real-time sensor feedback and environmental alterations, ensuring the vehicle maintains the desired trajectory accurately. Like path planning, solutions for path following tasks encompass a wide spectrum, including classical control methods like the PID controller, kinematic controller [152]–[154], MPC controller [155]–[158], and extending to ML methods [149], [159]–[161].

In [154], an adaptive trajectory tracking control scheme, as shown in Fig. 6, is introduced with adjustable gains to facilitate adherence to predefined paths. The designed adaptive control gains aimed to streamline tuning efforts, augment the convergence rate of tracking errors, and elevate trajectory tracing performance. Meanwhile, the strategy proposed by [158] involves expert interventions with pre-existing LiDAR-derived maps to further improve performance. As for the ML methods, in the work presented by [159], error states relative to reference trajectories are determined using vehicle state data obtained from sensor fusion involving IMU and GPS with an EKF. A Neural Network (NN) is trained using IL methods with a dataset collected from human-controlled and MPC-controlled driving scenarios. Trained NN maps error

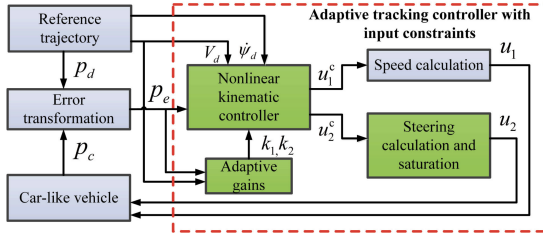


Fig. 6. Architecture of the proposed adaptive trajectory tracking control system in [154].

states to control commands. To avoid human-induced errors and large datasets, RL has also been widely adopted in path following tasks, as evidenced by [160], where the Deep Deterministic Policy Gradient (DDPG) algorithm is applied to guide an Autominy car along the desired path, aiming to minimize cross-track errors. Similarly, in the study by [149], a global policy is determined using DRL, while a local planner processes received images with another DRL agent to derive the final action for the path following. To address the data inefficiency challenges with RL, [161] then introduces a policy gradient-based policy optimization framework leveraging a first-principles model for path following task with a JetRacer. This framework facilitated the learning of precise control policies with limited real-world data.

C. Lane Keeping

Next, we discuss another fundamental driving behavior for small-scale vehicles, lane keeping, which has been a pivotal focus in extensive research across various platforms [7], [10], [11]. While the lane keeping task shares similarities with the path following, there are distinct differences between the two. Path following involves adhering to a predetermined path and utilizing real-time feedback to maintain desired trajectories safely. On the other hand, the objective of the lane keeping task is to guide the small-scale vehicle within the designated lane, conforming to specific tolerances for deviation from the lane center. This task requires the small-scale car to implicitly follow a path dynamically defined by the vehicle in real time. Consequently, this task predominantly relies on visual input, utilizing RGB cameras to monitor the position within the lane continuously. According to the methods used, we categorize research works into two groups, traditional methods and ML-based methods.

1) *Traditional methods*: Traditional methodology typically comprises two integral components: perception and control, similar to various other driving tasks. The perception module is responsible for processing sensor data, often obtained from cameras, to extract crucial information necessary for lane keeping. It can be divided into two parts, lane detection for analyzing the sensor data to identify and track lane markings on the road; and feature extraction for calculating relevant metrics such as lateral deviation and orientation deviation to determine the position of the car within the lane. The control module then utilizes the information extracted from the perception module to regulate the trajectory and ensure it remains within the designated lane. Control algorithms such

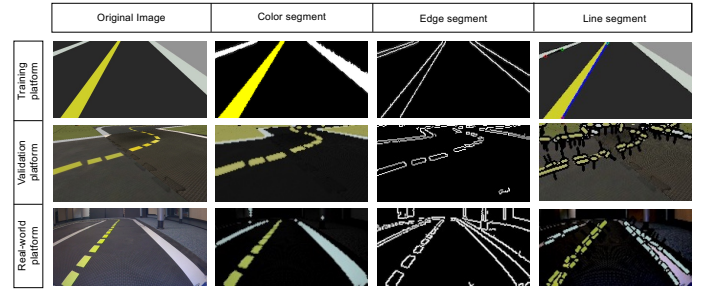


Fig. 7. Different outputs of the multi-step image processing pipeline proposed by [7] and later employed in [94], [95]. It starts from the image input from the camera, proceeds to detect road markings according to the color with HSV thresholding, detects marking edges with canny filter, and finalizes with detection marking used to estimate the lateral displacement and angle offset.

as PID controllers or other rule-based systems are employed to interpret the deviation data and adjust the steering angle accordingly.

In [7], a multi-step image processing pipeline, shown in Fig. 7, is devised to address the lane keeping task for Duckietown using traditional computer vision methodologies. With k-means clustering, Canny filter [162], Hue-Saturation-Value (HSV) colorspace thresholding, and probabilistic Hough transform [163], individual line segments are extracted, afterwards, A nonlinear non-parametric histogram filter is employed to estimate the lateral displacement concerning the right lane center and the angle offset relative to the center axis. These estimates hold immense significance within the lane-keeping task, serving as critical inputs for the subsequent control module. The control module employs a PID controller, utilizing these estimated parameters in real time to minimize deviations and steer the vehicle along optimal trajectories within the designated lane. Later [164] presents another similar pipeline for the Donkeycar platform, in which the H layer of HSV colored image is used to go through Gaussian kernel filter for noise filtering and Sobel edge detector [165], following the probabilistic Hough transform for lane detection. Then a list of rules is proposed to compute the steering angle for the car based on the detected lines. While traditional methods serve well for basic detection and control tasks, their limitations in generalization prompt the need for more advanced methodologies.

2) *ML-based methods*: Similar to the other driving tasks, ML-based methods are used to improve lane keeping capabilities and their generalization. Here, we divide them into two subcategories, namely modular system and end-to-end system, as in Fig. 2.

a) *Modular system*: For the lane keeping task, an ML-based modular system typically replaces traditional perception or control systems with more sophisticated ML-based algorithms. In [166], Convolutional Neural Network (CNN) models are used to predict the lateral displacement and the angle offset. These predictions were then used in conjunction with the lane filter and PID controller derived from [7] to control the Duckiebot. Besides replacing the perception module, [94], [95] use the same perception module from [7], but replaces the traditional controller with DRL algorithms

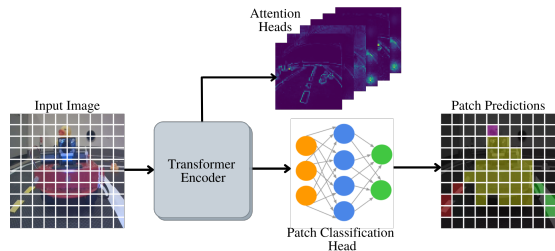


Fig. 8. In [168], image patches are encoded using a ViT and predict a class label for each patch. Then, the coarse segmentation output is used for a potential-field based controller.

that use the outputs from the perception module and achieves better performance than simple PID controller with multitask driving, not only lane keeping. With this modular system, the Sim2Real capabilities of the Duckiebot are also improved. For the Sim2Real capabilities improvement or generalization, [43] presents a modular system specifically tailored for lane keeping tasks. First, the perceptual system is trained with a mixture of simulation and real world datasets and map images into a shared latent space. Then, a list of DRL algorithms is employed, utilizing these latent features as inputs to control the Donkeycar. Furthermore, the evolution of transformer architectures, particularly the Vision Transformer (ViT) [167], has gathered increasing interest, competing with conventional CNN. For lane keeping tasks, for instance, in the work by [168], a pre-trained ViT is employed as a backbone network, see illustration in Fig. 8. This ViT model is further fine-tuned using limited datasets obtained from the driving environment to generate segmentation of the environment. Subsequently, a potential-field-based controller utilizes the segmentation output generated by the ViT as input and produces steering commands for control.

b) End-to-end system: A more highly researched system is the end-to-end system for lane keeping tasks, in which the agent receives raw sensor input and output control commands for lane keeping tasks. This control framework encompasses both IL and DRL. IL involves the system learning from expert demonstrations or human-driven data to emulate behaviors, decision-making, and actions observed in provided training demonstrations. Common IL algorithms include Behavioral Cloning (BC) [169], Generative Adversarial Imitation Learning (GAIL) [170], Inverse Reinforcement Learning (IRL) [171], Dataset Aggregation (DAGger) [172], and others. Since BC is a straightforward approach in IL that involves training a model to mimic expert behavior by directly mapping observed states to corresponding actions without understanding the underlying decision-making process, it is one of the foundational algorithms used for lane keeping tasks. For example, in [49], [173], CNNs are trained with image data to predict directly the steering angle for control under various evaluation metrics within the DeepRacer platform. However, the most crucial drawback of BC is the compounding errors, especially when the model encounters states not seen during training, leading to divergence from expert behavior. It is sensitive to errors in

the training data and might not capture the nuanced decision-making aspects of the expert. To improve the generalization and transferability of Sim2Real in the Donkeycar platform, [92] proposes incorporating uncertainty during training. Similarly, [174] augments the dataset by image style transfer [175]. BC, GAIL, and DAGger are compared by [176] within the Duckietown environment, and apply Domain Adaption to facilitate the Sim2Real transfer issue. In addition to IL, DRL stands out as another commonly used method with raw sensor data as input. [10], [177], [178] employ raw images directly into DRL controllers, while to speed up convergence, [99], [179], [180] preprocess input images, employing simple techniques to reduce input dimensions. For enhanced control smoothness, [181] combines Conditioning for Action Policy Smoothness (CAPS) with RL, addressing jerky control issues. For Sim2Real transfer capabilities, [38] includes delays and sampling rate as additional agent observations at training time to improve the robustness of DRL policies for Sim2Real transfer of the DeepRacer platform. Additionally, besides image inputs, raw LiDAR data serves as input in studies such as [47], where DRL algorithms navigate an F1TENTH car within structured environments using raw LiDAR input.

To further enhance convergence speed and boost generalization capabilities, the end-to-end systems often integrate autoencoders [182]. It consists of an encoder and a decoder: the encoder compresses input data into a lower-dimensional representation through a sequence of neural network layers, while the decoder reconstructs the original input from the compressed representation in the latent space. The training objective of an autoencoder is to minimize the difference between input data and the reconstructed output. This encourages the network to learn an efficient representation of the data in the latent space, subsequently utilized as input for control networks. As outlined in [183], [184], autoencoders are initially trained to compress image data into lower-dimensional representations. Following this compression, BC is employed to train Duckiebots using expert trajectories. Autoencoders are frequently integrated with DRL algorithms, for example, [42], [185] utilize variational autoencoders (VAE) [186] to compress images and use the resulting latent features as inputs for DRL algorithms. This approach, compared to DRL algorithms with raw image inputs, demonstrates faster convergence and improved learning efficiency.

D. Car following and overtaking

Among the previously mentioned tasks, car following and overtaking with small-scale cars remain relatively understudied areas. Nonetheless, they hold significant importance for research on autonomous small-scale vehicles.

1) Car following: Car following maneuver is the capability of an autonomous vehicle to maintain a safe and appropriate distance from the vehicle ahead while driving on the road. It requires the vehicle to track and follow the movements of the leading vehicle, adjusting its speed and position accordingly to ensure a safe, comfortable, and efficient driving experience. The existing literature on car following maneuvers with small-scale cars is relatively scarce, with a few notable studies

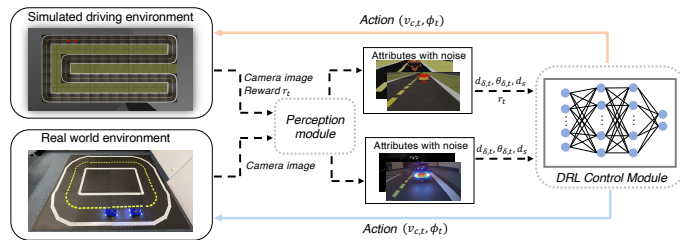


Fig. 9. Framework proposed in [95], the perception module leverages camera images to produce impact attributes regarding the environment, then the DRL control module utilizes the information to control the agent perform car following behavior.

standing out. A DDPG algorithm with an extended look-ahead approach is proposed in [187] for longitudinal and lateral control within vehicle platooning scenarios. For perception, LiDAR technology gauges inter-vehicle distance, while an IMU provides acceleration data. Additionally, a V2V system employing Wi-Fi communication transmits leader information to the follower vehicle. Similarly, in [188], a Cooperative Adaptive Cruise Control (CACC) system is implemented utilizing Deep Q-learning (DQN) [189]. This system enables the follower vehicle to dynamically adapt and maintain appropriate inter-vehicular distances. Notably, both these studies rely on V2V communication to achieve effective car following behavior. In contrast, [95] introduces a new perspective by realizing multitasking driving, encompassing car following and lane keeping, solely relying on visual sensors without the need for communication with other vehicles. In this approach, a pattern of circles is affixed behind the leading Duckiebot, aiding the ego Duckiebot in sensing distance and speed to mimic human driver behavior. A modular system is deployed, where the perception module extracts compact affordance information, and a DRL algorithm controls the Duckiebot based on this information. Despite its simplicity, this system yields promising results. As an imperative area for advancement, future research should emphasize car following behavior with small-scale cars, aiming to establish a foundational basis for real-world driving applications.

2) *Overtaking*: Overtaking refers to the maneuver where an autonomous vehicle changes lanes or positions itself to safely pass another vehicle traveling in the same direction on the road. The purpose of overtaking is to move ahead of the slower vehicle safely and efficiently while maintaining proper traffic flow. For scaled cars, it is a challenge to obtain the overtaking maneuver, since during the whole process, a precise localization system is required to avoid collision with the slower vehicle. Therefore, there are just a few papers focusing on the overtaking task with small-scale cars. A first contribution comes from [94], where authors employ a modular system equipped solely with onboard sensors to execute diverse driving tasks, encompassing lane keeping and overtaking for Duckiebots. The framework leverages traditional machine vision technologies to acquire compact affordance information, as discussed in [7], and utilizes LiDAR sensors for distance estimation relative to other vehicles. Afterward, the Long Short-Term Memory Soft Actor-Critic (LSTM-SAC)

algorithm assumes the role of the controller. Notably, LSTM aids the agent in recognizing distinct phases within the overtaking process. Demonstrated results affirm the efficacy of this proposed framework, managing both lane keeping and overtaking tasks, and showcasing superior performance when benchmarked against baselines. Another work regarding the overtaking task is [190], where a dual control approach with MPC towards active uncertainty reduction is proposed. This approach automatically balances the exploration-exploitation trade-off, enabling the MuSHR car to actively minimize uncertainty concerning the hidden states of other agents without compromising expected planning performance. The difference compared with [94] from the hardware side is that the vehicle being overtaken will yield, and the usage of a known grid map of the track. The exploration of overtaking tasks remains relatively limited within current research, signaling a crucial need for further investigation and focus in the future.

E. Obstacle Detection and Avoidance

Obstacle detection and avoidance refers to identifying and navigating around obstacles or potential hazards in its path to ensure safe and uninterrupted driving behavior. It utilizes various sensors, including cameras, LiDAR, ultrasonic sensors, and other technologies, constantly scan the surroundings to detect and classify obstacles. An effective obstacle detection algorithm necessitates a range of essential abilities. In this paper, obstacle detection algorithms are divided into different groups according to the usage of different sensors, we discuss the most widely used two: camera and LiDAR sensors.

1) *Vision-based approach*: The vision-based approach relies on images captured by cameras as the primary input for detection. This approach employs computer vision (CV) or ML algorithms, prominently leveraging CNN, for effective detection tasks. Within the realm of cameras used, the vision-based approach can be categorized into two subclasses: monocular and stereo. Monocular image-based methods rely on a single image for processing, while stereo methods utilize images captured by two synchronized cameras. Details about the camera sensors are discussed in Section IV-A.

Within monocular image-based methods, as outlined in [191], the obstacle detection task for small-scale cars is typically categorized into three primary domains: *appearance-based*, *motion-based*, and *depth-based* methods. With *appearance-based* methods, obstacles are typically identified as the foreground within images. The primary challenge lies in distinguishing relevant foreground or background elements based on established criteria, such as color discrepancies [192] or texture features [193]. In the work by [36], the RGB images captured by the monocular camera of a Duckiebot are initially transformed into the HSV colorspace. Subsequently, the color filter from OpenCV is employed to detect obstacles based on color differences. However, the drawback is evident: success detection depends on the predefined color of the obstacles, limiting adaptability to diverse scenarios. *Motion-based* obstacle detection refers to identifying obstacles or objects in an environment by analyzing motion vectors in the image, it involves comparing successive frames of images to

determine alterations in position, velocity, or other motion-related characteristics. Objects that move or exhibit changes in their motion characteristics are then identified as potential obstacles. Optical flow analysis [194], background subtraction, differential methods, can be employed for motion-based obstacle detection [195], [196]. *Depth-based* methods utilize depth information extracted from images to discern the distances and spatial arrangement of objects within the environment, aiding in accurate object detection [197], [198]. Employing conventional image processing techniques like this may fall short in meeting real-time application expectations, primarily due to their inability to swiftly adapt to dynamic conditions. Therefore, recent research endeavors have pivoted towards enhancing obstacle detection speed by employing CNN and particularly emphasizing the effectiveness of You Only Look Once (YOLO) [199]. YOLO is specifically designed for real-time object detection, and its variations have been employed to enhance success rates [200]–[202]. CNN offers promising capabilities in overcoming the limitations of traditional methods, showcasing greater adaptability and improved real-time performance in diverse and dynamic environments. However, given the restricted computational power available in small-scale cars, a balance must be achieved between accuracy and processing time. In [65], YOLOv3 and Tiny YOLO are selected as detection algorithms for the Go-CHART platform. [203] integrate GhostConv to the YOLOv4-tiny model to achieve faster detection, while in [204], YOLOv5 is used to detect cones and duckies within the Duckietown environment. Stereo image-based methods work by using a dual-camera system that captures images from slightly different angles, similar to the human binocular vision. This setup helps in perceiving depth and reconstructing three-dimensional scenes by analyzing the differences between the images from these cameras [205]. However, in the context of small-scale cars, constraints such as cost considerations and limited space availability restrict the usage of stereo cameras to select platforms, notably including RACECAR [18] and Autominy [23].

2) *LiDAR-based approach*: In addition to camera-based approaches, LiDAR is also widely used for obstacle avoidance systems. The applications of 2D LiDAR are prevalent in compact car platforms due to factors like size, price, weight, and overall compactness considerations. However, due to the existing computational limitations of these car platforms, innovative LiDAR data processing methods are often unavailable. Consequently, raw LiDAR point cloud data or minimally processed data is frequently used, involving procedures like imputing empty samples and cleansing noisy data, to serve as input for neural networks executing subsequent control tasks. In [48], the process of obstacle detection hinges on identifying the minimum value derived from a cluster of LiDAR points, following the determination of the position of the obstacle, a global path is generated and the vehicle is directed using MPC. After performing data cleaning, the minimum value obtained from the point cloud is adopted in [206] as the distance measurement to a potential collision object. Subsequently, a series of control command policies are executed based on this distance value. In [12], Follow the Gap (FTG) method [207] is employed for object detection and avoidance of

an F1TENTH car. This technique involves computing the maximum gap present within the LiDAR point cloud and subsequently determining the steering control command. This command is derived from the heading angle directed toward the center of the largest gap to the orientation of the ego car, guiding the car toward the direction of the maximum gap center.

F. Traffic sign recognition

Traffic sign recognition can be seen as a special element of object detection tasks, requiring vehicles to initially detect and identify traffic signs before responding appropriately to a diverse array of road signs and signals. Unlike the generic object detection task, traffic sign recognition uniquely relies solely on cameras. This dependence stems from the necessity to detect and classify the visual characteristics of traffic signs. The process typically commences with dataset acquisition, wherein cameras capture traffic signs for later utilization. These captured images undergo a series of preprocessing steps to refine quality, eliminate noise, adjust lighting, and employ data augmentation techniques. Subsequently, ML models [208]–[210] are trained using these compiled datasets for detection and classification. However, research on traffic sign recognition is limited for small-scale cars due to the unavailability of standard datasets that may differ across platforms. Hence, researchers must prioritize dataset collection as an initial step to train the networks. Future research should intensify exploration in this direction, particularly focusing on mixing traffic sign recognition with other driving tasks like navigation, lane keeping, or path following.

G. Racing

Autonomous racing represents a distinctive facet of autonomous driving research, demanding vehicles to leverage intricate algorithms, a suite of sensors, and cutting-edge control systems. This specialized form of driving involves navigating tracks, engaging in competitive races, and overcoming dynamic racing challenges. Unlike standard driving tasks, racing pushes vehicles to attain high velocities, extensively testing the dynamic limits of these automated systems. When racing at high speeds, vehicles must swiftly detect other vehicles or obstacles, demanding rapid reaction times. Additionally, they must accurately localize their position concerning the track and strategize dynamic trajectories to optimize performance [211]. While extensive research has been dedicated to full-size racing competitions like Roborace [212], our primary focus centers on small-scale car racing events such as AutoRally [9], F1TENTH [12], Donkeycar [11], ORCA [15] and others.

1) *Modular system*: In this section, we will explore the racing task using the modular system, which similar to other tasks, primarily comprises two essential modules: the perception and control modules. The perception module plays a critical role in racing tasks as it assists the vehicle in determining its position on the racetrack. In the racing context, swift and accurate reactions are essential to fulfill subsequent control tasks. Thus, a racing-specific perception module must balance speed and precision to enable quick and accurate

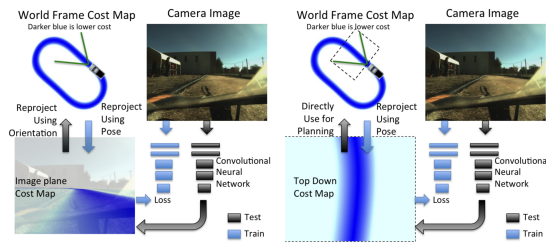


Fig. 10. In [56], the cost map of the track in front of the vehicle is predicted with CNN.

responses during racing scenarios. For this task, the most commonly used perception module is the fusion with GPS and IMU as discussed in Section III-A. However, when states or sensor measurements that are not approximately linear in the measurement time frame, [9] and [51] use factor graphs combined with incremental smoothing and mapping 2 (iSAM2) [213], to fuse GPS and IMU measurements and output smoothing estimation. For the issues with non-linear dynamics and non-linear measurement models, [53]–[55] use the particle filter to fuse the camera images with IMU, and GPS. Additionally, a single camera can serve as a perception sensor for racing tasks. For example, in [56], CNN is used with a single monocular camera to predict the cost map of the track in front of the vehicle which is directly useable for online trajectory optimization with MPC. Similarly, [214] uses a top-down lane cost map CNN and the YOLOv2 CNN to extract feature-input values and a two-point visual driver control model (TPVDCM) as the controller to control the vehicle.

Same as the perception module, the control module also has a high demand for timely reactions, often surpassing the importance of the perception module. The most commonly used control module in racing is MPC, which is a control strategy that utilizes a dynamic model of the system to predict its future behavior and make control decisions based on optimization criteria. In [15], the authors use onboard IMU sensors and a global localization system to acquire the states of the car within the ORAC platform. Subsequently, a path planner and a Nonlinear MPC (NMPC) are utilized to guide the racing process. Later, in [51], a sampling-based MPC algorithm called the Model Predictive Path Integral Control algorithm (MPPI) is introduced for Autorally. This algorithm presents a novel derivation of path integral control, offering an explicit formula for controls across the entire time horizon. A notable attribute of MPPI is its capability to generate entirely new behaviors dynamically, enabling the controller to drive the vehicle to its operational limits. Then, a few improved versions are proposed, such as the robust sampling-based MPC framework based on a combination of model predictive path integral control and nonlinear Tube-MPC [215] and best response model predictive control based on a combination of the game-theoretic notion of iterated best response, and an information-theoretic model predictive control algorithm [216]. When the dynamic model lacks perfect accuracy, it introduces potential disparities between the predicted and actual behavior of the system. To address this challenge, Learning

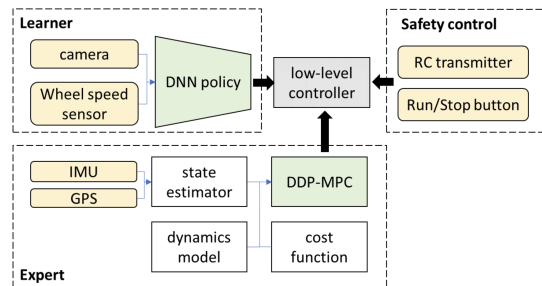


Fig. 11. End-to-end IL system used in [91] for an Autorally racing car.

Model Predictive Control (LMPC) integrates learning algorithms with MPC, aiming to refine control strategies in the face of uncertain or changing dynamics. Compared to traditional MPC, LMPC continually enhances its performance, especially in scenarios where complete knowledge of system dynamics is unavailable or subject to variation. The learning mechanism algorithms such as RL, Gaussian processes, neural networks, or other adaptive learning methods in LMPC continuously update the predictive model based on collected data and feedback from the system, to achieve better performance, adaptability to changing system dynamics, and robustness in scenarios where precise models might be unavailable or incomplete. [53] establishes the connection between MPC and online learning, and proposes a new algorithm based on dynamic mirror descent (DMD) and MPC (DMD-MPC), which provides a fresh perspective on previous heuristics used in MPC. In [217], historical data is used to construct secure sets and approximate the value function, facilitating LMPC to learn and improve from past experiences within BARC platform. Later, [218] applies Gaussian processes to correct the model mismatch, then uses MPC for tracking pre-computed racing lines using this corrected model for an F1TENTH car. For more responsive control, [110] uses Linear Parameter Varying (LPV) theory to model the dynamics of the vehicle and combine it with MPC (LPV-MPC), which can be computed online with reduced computational cost. To swiftly identify unsafe conditions, [54] propose a Perceptual Attention-based Predictive Control (PAPC) algorithm, where MPC is first used to learn how to place attention on relevant areas of the visual input and ROI, and output control actions as well as estimates of epistemic and aleatoric uncertainty in the attention-aware visual input of an Autorally car. [219] introduces a local, linear, data-driven learning method for error dynamics within the LMPC framework. This approach exhibits increased robustness against parameter variations and limited data compared to prior LMPC implementations. Pure pursuit is another control algorithm used in racing tasks [220]. A key limitation in model-based control methods is that they require localization during the race, where the motion capture system is sometimes used [221], [222], but it is still limited by requiring a map of the track or a set of cameras and the hardware requirement for real-time localization.

2) *End-to-end system*: In addressing the challenges within modular systems and enhancing racing performance, various studies have proposed an end-to-end system that incorporates

methodologies such as IL and RL [223]. The authors in [91] introduce an end-to-end IL system depicted in Fig. 11, where a learner network needs to imitate an expert. The expert fuses GPS and IMU for state estimation and uses an MPC as controller, the learner uses a DNN as control policy to map raw, high-dimensional observations to continuous steering and throttle commands. [224] presents a deep imitative RL framework for end-to-end racing with camera input, where IL is used to initialize the policy, and model-based RL is used for further refinement by interacting with an uncertainty-aware world model. To improve the stability of the racing system, [225] designs a residual control system, in which multiple Bayesian Neural Networks (BNNs) are trained with two camera inputs and GPS measurements to control an Autorally car in an end-to-end fashion. Incorporating LiDAR technology into end-to-end systems has also garnered attention. A model-based RL approach is employed in [226] using raw LiDAR input on the F1TENTH car to navigate racetracks effectively. Subsequently, in [227], LiDAR data is used as input for DQN to control the F1TENTH car. This study also provides a comparative analysis between neural network methodologies for processing LiDAR data and evaluates two Sim2Real approaches. Although RL can be used for racing tasks, the well-known low sample efficiency issue still holds back further development. For this issue, [228] propose an efficient residual policy learning method with the raw observation of LiDAR and IMU, in which first a controller based on the modified artificial potential field (MAPF) is used to generate policies, then DRL algorithms are used to generate a residual policy as a supplement to obtain the optimal policy with increased efficiency. Similarly, [229] presents a trajectory-aided learning (TAL) method that trains DRL with raw LiDAR input by incorporating the optimal trajectory into the learning formulation. [230] also presents a residual vehicle controller that learns to amend a traditional controller with a similar idea. To tackle the safety issues that usually occur in RL training, [231] uses a Viability Theory-based supervisor to recursively feasible vehicle safety during the training. Furthermore, to improve the robustness of RL, [232] first train a teacher model that overfits the training track, moving along a near-optimal path, then use this model to teach a student PPO model the correct actions along with randomization.

3) *Drifting*: Autonomous drifting can be seen only as a facet of racing, but also as an individual task within autonomous vehicle control. This maneuver is characterized by intentionally inducing oversteer, resulting in the rear tires losing traction and enabling the vehicle to elegantly slide or "drift" through a turn. Autonomous drifting requires advanced control systems and algorithms that can precisely manage the speed, steering, throttle, and braking to maintain control while deliberately sliding through a corner. Few studies work on the drifting problems for small-scale cars, the key point is the awareness of the kinematic model and dynamic of the vehicle and the accurate estimation of the state such as position, and steering, to control the car appropriately. For instance, [8] uses a dynamic bicycle model for a BARC car, which has a single rigid body model with lumped rear wheels and front wheels. Then EKF is utilized to fuse the sensor measurement

from IMU and encoders with the dynamic bicycle model and Pajeka tire model [233]. Moreover, optical flow is used to estimate the velocity, and a Linear-quadratic regulator (LQR) controller with designed equilibrium drifting points is used to control the vehicle. Later in [234], EKF is also applied for state estimation but with a six-state bicycle model with linear front and rear-wheel tire forces. In most cases, an accurate vehicle dynamics model is often elusive. Hence, [235] proposes an approach to tackle the drifting park problem with BARC cars by segmenting it into distinct phases: the normal driving regime and the sliding regime. During the normal driving phase, a nonlinear MPC operates with a predefined kinematic model. As the vehicle transitions into the sliding phase, reliance on this model diminishes. To navigate this shift, a feedforward-feedback controller takes charge, orchestrating safer maneuvers adeptly under sliding conditions. Another challenge in previous studies pertains to the singularities embedded within popular tire models. Specifically, these models exhibit singularity issues, notably with tire slip angles becoming singular at lower vehicle speeds due to the presence of the vehicle velocity term in the denominator. In response, [236] introduces a fused kinematic-dynamic bicycle model accompanied by a nonlinear MPC system for a RACECAR. This pioneering approach harmonizes the planning and execution of dynamic vehicle maneuvers within a unified framework, optimizing the entire process cohesively.

Although autonomous racing does not commonly occur in daily driving scenarios, it is still an emerging field in intelligent vehicles and transportation systems. The intriguing aspect lies in the operation of autonomous small-scale cars pushing the boundaries of vehicle capabilities [211]. Operating at high speeds with minimal reaction time within dynamic environments, autonomous racing with small-scale cars emerges as a compelling area within the autonomous driving domain.

H. Cooperative driving

In comparison to the scenarios mentioned before which typically only involve one controlled vehicle, cooperative driving refers to a collaborative approach where multiple autonomous vehicles interact and communicate with each other to achieve common goals, navigate shared spaces, and enhance overall traffic efficiency and safety. It relies on vehicles exchanging information, such as their positions, speed, intended trajectories, and other relevant data, to make collective decisions. The decision-making processes of cooperative driving include *centralized control* and *decentralized control*. In the *centralized control* system, a central controller oversees and coordinates the actions of all vehicles involved in the cooperative driving system. This central entity collects data from all vehicles, processes the information, and makes decisions. On the contrary, in a *decentralized control* system, decision-making is distributed among individual vehicles within the environment. Each autonomous vehicle makes independent decisions based on local information gathered from its sensors and communication with nearby vehicles. The vehicles negotiate and collaborate among themselves, sharing relevant data and coordinating actions to achieve common goals.

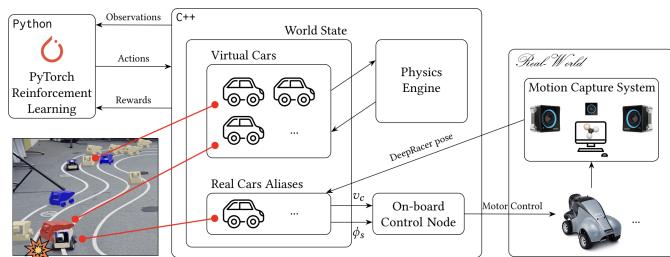


Fig. 12. Overall schematics of the multi-vehicle, mixed reality RL approach in [41]. Both virtual and real DeepRacer vehicles exist within the simulation that manages the physics of the virtual cars and emulates collisions in mixed reality.

Examples of cooperative driving encompass various aspects, spanning from mapping, path planning, obstacle avoidance to roundabout navigation, and traffic jam mitigation. For example, in the study by [237], a feature-based map registration method is utilized for a collaborative SLAM system. Three distinct vehicles collaborate, enhancing SLAM efficiency by achieving faster mapping capabilities through collaborative efforts. In the work by [238], a multi-vehicle path planning strategy Enhanced Conflict Based Search with Task Assignment (ECBS-TA) [239] is employed for MuSHR cars. It involves optimal task assignment considering discrete workspace representation. Following this, collision-free trajectories are planned for all vehicles using decentralized MPC for precise path tracking. Addressing safety concerns, [240] devises a distributed priority assignment algorithm called priority-based non-cooperative distributed model predictive control (P-DMPC). This algorithm elevates the priority of a vehicle based on the number of potential collisions anticipated along its planned trajectory, thereby enhancing safety in multi-vehicle scenarios. [41] introduces a mixed reality framework depicted in Fig. 12 tailored for safe and efficient RL driving policies in multi-vehicle systems. This setup includes one physical vehicle and sixteen virtual vehicles. The RL agent demonstrates capabilities in lane keeping and obstacle avoidance within this complex multi-vehicle environment. In the case of navigation through a roundabout, the vehicles employ cooperative strategies to merge into the appropriate lane within the roundabout by communicating their intentions to enter the roundabout and negotiate their entry sequence. Vehicles need to follow certain merge and yield protocols, which for example vehicles yield to others already within the roundabout, vehicles inside the roundabout adjust their speeds and trajectories. To achieve this scenario, [59] utilizes RL algorithms to control a set of miniature cars successfully coordinated at a roundabout and ensure a smooth merge, and demonstrates the results in University of Delaware’s Scaled Smart City (UDSSC) testbed. Later, [57] develops a decentralized optimal control framework for 9 cars in a multi-lane roundabout in UDSSC and eliminates stop-and-go driving while preserving safety.

Another driving scenario to discuss is traffic jam mitigation, which remains a focal point in cooperative driving, emphasizing the collaborative endeavors among multiple autonomous vehicles to prevent or alleviate traffic congestion.

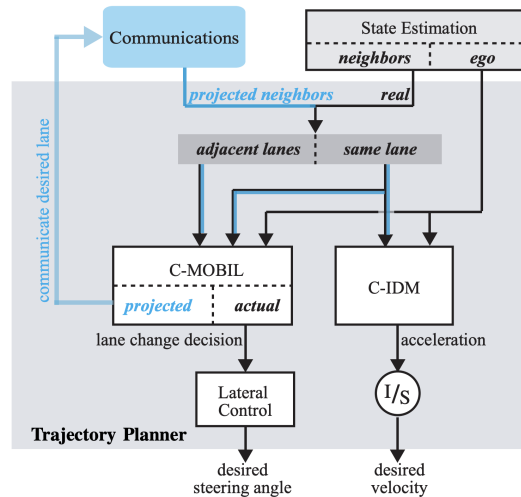


Fig. 13. Diagram of trajectory planner with C-MOBIL and C-IDM in [66]. The ego vehicle plans a trajectory and velocity profile based on its state and the actual state of the neighboring vehicles.

The primary goal is to sustain optimal traffic flow and speed, particularly in unexpected scenarios such as abrupt braking or lane closures. This requires vehicles to coordinate actions collectively and respond to dynamic environmental changes. For instance, [66] introduces a framework that modifies the intelligent driver model (IDM) [241] and the MOBIL lane change model [242] for cooperative driving. Additionally, [243] and [244] propose decentralized optimal traffic control methods. Their approaches demonstrate reduced travel times compared to baseline scenarios involving human-driven vehicles lacking connectivity. [24] presents the CoRoLa Car Platform, and achieves multi-vehicle platooning driving with Adaptive cruise control (ACC). Furthermore, recent research has explored human-robot cooperation ([245], [246]), as well as collaborations between Unmanned Ground Vehicles (UGVs) and Unmanned Aerial Vehicles (UAVs) [247]. These studies delve into cooperative methodologies between different vehicle types, fostering improved traffic management and congestion mitigation through collaborative efforts.

IV. SENSORS AND SENSOR SYSTEMS

In Section II-A, various platforms are explored, each employing diverse sensors to perceive their surroundings and execute the tasks detailed in Section III. Following that, we discuss the most commonly utilized sensors across these platforms, providing their respective use cases.

A. Camera

An RGB camera provides a stream of information that is easily processed and understood by humans. This helps researchers to better understand the perspective of the robot. The amount of information provided by cameras is huge, which allows the robot to perceive a lot of information with just one sensor in a short amount of time. The downside of this is, that they need a high bandwidth communication link to whichever part of the robot needs those information. Also

TABLE II
OVERVIEW OF RESEARCH IN DIFFERENT TASKS FOR SMALL-SCALE CARS.

Task Category		Method	References	
Localization and Mapping		KF	[108]–[110], [219]: BARC; [111]: QCar	
		PF	[45]: FITENTH; [114]: RACECAR	
		GMapping	[122]: Roborace; [123], [125]: -	
		HectorSLAM	[119]–[121]: -	
		Cartographer	[248]: FITENTH; [127]: Innopolis UGV; [126], [128]: -	
		GALNet	[133]: Autominy	
		PACT	[134]: MuSHR	
		LoFTR	[135]: Jetbot	
Path planning	Classical	Dijkstra’s algorithm	[142]: -	
		Hybrid A star	[143]: QCar	
		GA	[145], [146]: -	
		RRT	[147]: RACECAR	
	ML-based	RL	[149]: Jetbot; [150]: MuSHR; [98]: Duckiebot; [148]: -	
		BRPO	[151]: MuSHR	
Path following		IL	[249]: Donkeycar	
		Kinematic controller	[154]: QCar; [152], [153]: -	
		MPC	[158]: MuSHR; [155]–[157]: -	
		IL	[159]: ART/ATK	
Lane keeping		DRL	[160]: Autominy; [161]: JetRacer	
		Classical	classical CV + PID	[7], [250]: Duckiebot
			classical CV + rule-based	[164]: Donkeycar
		ML-based	CNN + PID	[166]: Duckiebot
			classical CV + RL	[94], [95]: Duckiebot
			CNN + RL	[43]: Donkeycar
			ViT	[168]: Duckiebot
			IL (raw input)	[49], [173]: DeepRacer; [92], [174]: Donkeycar; [176]: Duckiebot
			RL (raw input)	[10], [38], [177], [178], [181]: DeepRacer; [99], [179]: Duckiebot; [180]: JetRacer; [47]: FITENTH
			IL (autoencoder)	[183], [184]: Duckiebot; [251]: -
RL (autoencoder)	[42]: Donkeycar; [185]: Duckiebot			
Obstacle Detection		Appearance-based	[36]: Duckiebot	
		Vision-based	Motion-based	[195], [196]: -
			Depth-based	[197], [198]: -
			CNN	[65]: Go-CHART; [203]: JetRacer; [204]: Duckiebot; [252]: Jetbot; [253], [254]: -
		LiDAR-based	Minimum value	[48], [206]: FITENTH
			FTG	[12]: FITENTH
Racing		iSAM2 + MPC	[9], [51]: Autorally	
		Particle filter + MPC	[53], [55]: Autorally; [218]: FITENTH	
		Classical	CNN + TPVDCM	[214]: Autorally
			MPC	[15], [255], [256]: ORAC
			LMPC	[217], [219]: BARC
			LPV-MPC	[110]: BARC
			PAPC	[54]: Autorally
			Pure pursuit	[220]: TUNERCAR
			IL	[91]: Autorally
		End-to-end	BNN	[225]: Autorally
			RL	[226], [227]: FITENTH; [222]: ORAC; [224], [228], [229], [232]: -
Drifting			EKF, LQR	[8], [234]: BARC
			NMPC	[235]: BARC; [236]: RACECAR
Car following		DRL	[95]: Duckiebot; [187]: Donkeycar; [188]: QCar	
Overtaking		DRL	[94]: Duckiebot	
		MPC	[190]: MuSHR	
Traffic sign recognition		Classical	[37]: -	
		Tiny-YOLO	[210]: -	
Cooperative driving		Centralized control	[41]: DeepRacer; [59]: UDSSC; [24]: CoRoLa; [246]: Jetbot; [247]: QCar	
		Decentralized control	[237]: QCar; [238]: MuSHR; [240]: μ Car; [16], [57], [243], [244]: UDSSC; [66]: CamMini; [245]: Jetbot	

with the information in images being so densely encoded, it is difficult for a robot to understand the environment.

The field of computer vision has emerged as a crucial

scientific discipline, facilitating the extraction of pertinent details from images and videos. In recent years, the advent of

deep learning models, such as YOLO [199], has significantly contributed to enhancing the robot’s ability to interpret scenes captured by cameras. It is worth noting that cameras face external influences, such as varying lighting conditions, which can substantially alter the captured images. In extreme scenarios, such as very dark environments or instances where direct light affects the camera, the effectiveness of cameras may be compromised. A big advantage of cameras is their wide pricing range, starting from 15 USD, corresponding to images of different quality in regards to resolution and dynamic range. They are also easy to interface with, usually requiring only a USB connection. Some tasks can be accomplished only with cameras, e.g. traffic sign or road marking detection [210], [257], [258].

Beyond RGB cameras, more advanced options exist, including those detecting optical flow [259] or depth cameras [260], employing different methods to ascertain the distance to objects. These advanced cameras provide both depth information and standard RGB images. In the context of autonomous tasks for single-car platforms discussed in this paper, cameras emerge as a ubiquitous choice. Their cost-effectiveness and information-rich output make them the preferred sensor for many platforms. Among the commonly used cameras in scaled vehicles, the Raspberry Pi Camera stands out [7], [11], [22], [24], [29]–[31], [60], [61], [65], [73]. Designed for the Raspberry Pi, it combines affordability with decent image quality, offering a resolution of 1080p and a dynamic range of 44dB. Another popular option used in the discussed platforms are the Intel Realsense⁴ line of cameras [19], [21], [261]. Those include two cameras and an IR projector, which allow to capture not only an RGB image but also depth information of each pixel by means of stereovision. The IR projector helps to improve accuracy in scenes with poor textures. The manufacturer claims an accuracy in the centimeter range.

B. LiDAR

LiDAR, another widely employed sensor in numerous platforms, functions by measuring the time taken for a beam of light to reflect off a surface. This beam is emitted from multiple angles (typically ranging from 360 to 2048) around the LiDAR, creating a detailed map of points representing objects in the platform’s vicinity. There are also multi-layer LiDARs with laser beams spanning up to 128 angles, providing the platform with information about objects at different heights and generating a comprehensive 3D point cloud. Available in various resolutions, LiDARs offer enhanced information, particularly in intricate and structured environments. The typical scanning frequency of LiDARs ranges from 5 to 20 Hz, with high-end models reaching a detection range of up to 350 meters.

The distinct advantage of LiDAR over cameras lies in its direct identification of the platform’s surroundings, including the precise position of objects relative to the robot. In contrast, a camera first needs to identify an object in an image and then estimate its position. Moreover, LiDAR provides significantly more accurate positional information compared to estimations

derived from camera images. However, unlike cameras, LiDARs lack the ability to discern details such as the color of the detected objects. This limitation renders them unsuitable, for example, in tasks like traffic signs or lane detection. LiDARs also possess a notable advantage over cameras as they remain unaffected by environmental conditions such as varying lighting conditions, and they can operate effectively even in complete darkness. Additionally, certain LiDAR models provide information on reflectivity levels, enabling a rough distinction between different surface types. For instance, they can differentiate highly reflective road markings from less reflective obstacles. LiDARs are typically more expensive than cameras. The cheapest hobby LiDARs start at around 150 USD for a simple one plane sensor. But the prices quickly go up as the resolution or amount of planes increases.

Typically physically larger platforms use LiDAR sensors [8], [10]–[13], [18]–[21], [23], [60], [65], [261], [262] as they tend to be bigger and heavier than cameras. Those platforms are also usually more versatile and used for more different tasks and therefore the additional cost of a LiDAR is feasible. In our investigation, all platforms utilizing LiDAR also integrate a camera to address the limitations of LiDAR for specific tasks. The LiDAR that is used by far the most on the platforms we investigated is the single plane RPLIDAR⁵ [8], [11], [20], [21], [23], [60], [65], [261]. It offers a reasonable detection range of 12m and a resolution of 0.225 degrees for small scale car platforms with a 360 field of view. And is one of the cheaper options costing around 400 USD. But it only allows for a 10 Hz scan frequency. The second most popular, higher end solution is the Hokuyo UST-10LX [12], [18], offering a 270 degree field of view and a 10m detection range.

C. IMU and Encoders

Some sensors that are usually not used on their own but as an additional source of information for other sensors are IMU and odometry encoders. Where odometry encoders provide information about the angle by which each wheel of a robot has turned and therefore allow us to estimate where it has traveled, the IMU provides information on how fast a robot is spinning along each of its axes aiding in estimating the total rotation.

The information of these two types of sensors is usually combined with other absolute positioning inputs like a camera or a central localization system to fuse them in a filter like a Kalman filter [106] or in any other kind of perception module. IMUs are available at relatively affordable prices, ranging from 15 USD. The two IMU sensors most commonly used in the discussed platforms are the MPU9250 and MPU6050 [5], [7], [11], [21], [60], [261]. Although it has to be noted, that not all publications mention the exact model of the IMU used. Both sensors feature a 3-axis gyroscope, which measures the rotational speed, and a 3-axis accelerometer, which measures linear acceleration. The MPU9250 additionally offers a 3-axis magnetometer to incorporate measurements of the Earth’s magnetic field into orientation sensing.

⁴<https://www.intelrealsense.com/>

⁵<https://www.slamtec.ai/product/slamtec-rplidar-a3/>

Odometry encoders can be found in several different forms, ranging from magnetic encoders to optical ones. Their implementation is usually dependent on the platform, as they need to be tightly integrated into the mechanics of the robot. The encoders are usually below 10 USD. Almost all of the platforms we investigated used an IMU and some form of encoder as they are cheap and provide good position information, especially in slow indoor environments. The exception was the smallest platform, primarily designed for swarm robotic investigations [17], where extreme cost considerations led to the exclusion of these sensors.

D. GPS

GPS is the least frequently used sensor with model scale platforms [8], [9]. Most of the discussed platforms are designed for indoor use, which eliminates the use of GPS as the signal does not penetrate buildings. However, recognizing the pivotal role GPS plays in full-sized vehicles, many model-scale platforms opt to replace it with indoor central localization systems, as detailed in Section IV-E, to enhance realism. GPS receivers are also comparatively cheap at around 30 USD. However, for those seeking higher precision, the cost can escalate to several hundred USD, especially for the more advanced GPS RTK systems [263]. Such precision may become necessary for model-scale platforms, as conventional GPS systems typically only offer an accuracy of approximately 5 meters [264].

E. Central Localization system

In situations where the emphasis is on studying the interaction among multiple vehicles rather than individual vehicle behavior, a central localization system streamlines the task, allowing a more focused approach to other aspects such as obstacle avoidance or overtaking. By decoupling the algorithms for (multi) vehicle behavior from the perception of individual vehicles, central systems enable the study of system dynamics in an idealized "best case" scenario. In this context, the term "best case" refers to a situation where a vehicle possesses precise knowledge of its own position and that of surrounding obstacles. However, it is essential to acknowledge that this assumption may not align with the complexities of real-world road situations. Conversely, central systems find utility in simulating GPS positioning within actual vehicles.

One of the cheapest options implemented in the considered platforms involves the use of special markers or tags on each vehicle, which are observed by one or multiple overhead cameras [71]. These markers, based on ArUco [265] technology, are strategically placed on vehicles and key positions or obstacles. Knowing the intrinsic and extrinsic parameters of the cameras, existing libraries like OpenCV ⁶ can be employed to detect these markers and estimate their position and orientation. As discussed in Section IV-A, cameras are relatively inexpensive, and the markers merely need to be printed out. While the resulting localization precision is reasonable [266], it does decline with the distance of the markers from the

camera. Mitigating this issue involves the use of multiple cameras, necessitating synchronization and precise positioning of all cameras.

Off-the-shelf solutions for tracking also exist from various manufacturers, such as OptiTrack ⁷ or VICON ⁸. These solutions predominantly rely on high-speed IR cameras and reflective markers on the tracked objects. The systems inherently provide position and orientation information for different marker assemblies (referred to as rigid bodies) without requiring additional processing. Notably, the accuracy of these systems surpasses that of solutions utilizing RGB cameras, with manufacturers often specifying sub-millimeter accuracy. However, the upfront cost is relatively high, typically exceeding 10,000 USD, and in some cases, additional licensing fees for the requisite software may apply [16], [66].

F. Other sensors

Several platforms discussed in Section II-A employ additional sensors to either emulate sensors found in full-size autonomous cars or fulfill specific tasks.

A prevalent type of sensor utilized in many platforms [5]–[7], [21], [24], [29], [32], [33], [65], [67], [69], [267] is the single-point distance sensor, available as either ultrasonic or infrared. These sensors operate on the time-of-flight principle, measuring the time taken for a wave to bounce back into the sensor. Typically positioned at the front of vehicles, they often mimic radar sensors and play a crucial role in tasks such as car following.

Line following sensors, consisting of an array of light sensors aimed at the ground, are employed in certain platforms [16], [21], [21] to assist visual line following, with a camera serving as a secondary input. While these sensors can easily discern the line from the road, a limitation is their coverage area, which is relatively small and located underneath the car. If the vehicle deviates significantly from the line, the sensor may struggle to rediscover it.

One platform [71] utilizes RFID readers to detect specific points of interest on the road, such as the beginning of intersections or as indicators for turns on a crossroad. Another platform [6] employs cliff sensors, which function as downward-facing distance sensors, indicating if the part of the vehicle with the sensor is suspended over a steep drop. This sensor serves to prevent the vehicle from inadvertently falling off a precipice in the environment.

For platforms designed for use with multiple vehicles [6], [17], [30], [31], infrared (IR) transmitters and receivers are employed. These facilitate cost-effective communication between different robots.

G. Compute Units

To process the information from the sensors and compute actuator movement according to their task, the platforms require a dedicated computational unit.

The prevailing choice across numerous platforms [7], [11], [16], [21], [24], [30], [61]–[63], [66], [71], [261] is the

⁶<https://opencv.org/>

⁷<https://optitrack.com/>

⁸<https://www.vicon.com/>

Raspberry Pi single-board computer (SBC)⁹. Built on a System on a Chip (SoC), the Raspberry Pi features a compact physical size but offers modest computational performance, with a 4-core 1.5GHz CPU. Despite its relatively low processing power, the Raspberry Pi is well-suited for the majority of tasks performed by these platforms.

A comparable alternative to the Raspberry Pi is the Nvidia Jetson¹⁰. Also based on an SoC, the Nvidia Jetson stands out by incorporating an additional GPU to accelerate machine learning tasks. Given their similar connectivity, some platforms offer compatibility with either the Raspberry Pi or the Nvidia Jetson [7], [11], [261]. However, the majority of platforms exclusively support the Nvidia Jetson [12], [13], [18]–[20], [22], [60], [68], [73].

For platforms not requiring high computational performance on the vehicles themselves, microcontrollers [5], [17], [29], [32], [64], [67], [70], such as Arduino, are commonly employed. Although microcontrollers offer lower performance than Raspberry Pi, they enable real-time code execution, crucial for interfacing with low-level sensors and actuators. They also use less power and are cheaper.

Conversely, some platforms leverage regular PCs as their computational unit [9], [10], [262]. While PCs provide the highest performance, they have larger physical footprints and higher power consumption.

V. FUTURE TRENDS

In the previous sections, we have gone through the currently available small-scale car platforms, their hardware configurations, and the autonomous driving tasks achieved by these platforms. In pursuit of augmenting the capacity and applicability of these small-scale car platforms across diverse age groups, facilitating educational use for students, and supporting sophisticated research purposes, we list the following opportunities for further exploration.

Firstly, it is imperative to contemplate transforming the small-scale platform into a more widely accessible resource for educational purposes and academic research. This necessitates the establishment of a lower entry barrier, reduced pricing, and the implementation of a comprehensive learning pipeline. For educational usage, the first consideration should be given to the ease of learning and maintenance for teachers. A more user-friendly starting point will likely foster increased enthusiasm among educators, encouraging them to incorporate the platform into their daily teaching activities. This, in turn, will provide students with a challenging learning experience, ultimately preparing them for the intricacies of fully autonomous driving in the near future. For research applications, an in-depth exploration of the accessibility of the small-scale car platform is essential. This entails tailoring entry levels to accommodate various research goals, catering to individuals with zero experience in robotics to seasoned professionals. The platform should not only serve as a testbed for autonomous systems but also ignite enthusiasm for exploring

diverse robotic configurations. While some platforms currently offer support for different entry levels, a more comprehensive development is warranted to meet the diverse needs of the research community.

Secondly, regarding the more academic research consumption, the versatility of the platforms should be more considered. Specifically, concerning individual small-scale cars, attention should be directed towards enhancing their functional dimensions. In line with advancements in semiconductor technology, where computation and sensor units are becoming more compact yet powerful, platforms should incorporate more sophisticated sensors, thereby augmenting the overall capabilities of the system. Expanding the scope of research considerations, we propose a thorough examination of smart city configurations. While smart cities hold significant potential in advancing research on autonomous driving for small-scale cars, there exists a gap in terms of accessibility, reproducibility, and standardization of best practices. There is an urgent need for a common framework across the research community, encompassing both hardware and software aspects. Furthermore, existing smart city setups often overlook key elements such as weather conditions and pedestrian interactions, which are important in real-world driving scenarios. Addressing these factors in future research is essential for developing comprehensive and realistic autonomous driving solutions within smart city environments.

Thirdly, achieving fully autonomous driving necessitates the integration of critical technologies such as Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), and Vehicle-to-Everything (V2X). While these technologies have been extensively researched in the literature, there remains a noticeable gap in discussions of small-scale car platforms. Consequently, the community needs to pivot towards exploring and advancing V2V and V2I communications as the next steps in the pursuit of comprehensive autonomous driving solutions.

VI. CONCLUSION

In this paper, we offer an overview of the current state-of-the-art developments in small-scale autonomous cars. Through a detailed exploration of both past and ongoing research in this domain, we illuminate the promising trajectory for the advancement of autonomous driving technology with small-scale cars. We initially enumerate the presently predominant small-scale car platforms widely employed in academic and educational domains and present the configuration specifics of each platform. Similar to their full-size counterparts, the deployment of hyper-realistic simulation environments is imperative for training, validating, and testing autonomous systems before real-world implementation. To this end, we show the commonly employed universal simulators and platform-specific simulators. Furthermore, we provide a detailed summary and categorization of tasks accomplished by small-scale cars, encompassing localization and mapping, path planning and following, lane-keeping, car following, overtaking, racing, obstacle avoidance, and more. Within each benchmarked task, we classify the literature into distinct categories: end-to-end systems versus modular systems and traditional methods

⁹<https://www.raspberrypi.com/>

¹⁰<https://www.nvidia.com/de-de/autonomous-machines/embedded-systems/>

versus ML-based methods. This classification facilitates a nuanced understanding of the diverse approaches adopted in the field. The collective achievements of small-scale cars are thus showcased through this systematic categorization. Since this paper aims to provide a holistic review and guide, we also outline the commonly utilized in various well-known platforms. This information serves as a valuable resource, enabling readers to leverage our survey as a guide for constructing their own platforms or making informed decisions when considering commercial options within the community.

We additionally present future trends concerning small-scale car platforms, focusing on different primary aspects. Firstly, enhancing accessibility across a broad spectrum of enthusiasts: from elementary students and colleagues to researchers, demands the implementation of a comprehensive learning pipeline with diverse entry levels for the platform. Next, to complete the whole ecosystem of the platform, a powerful car body, varying weather conditions, and communications issues should be addressed in a smart city setup. These trends are anticipated to shape the trajectory of the field, contributing significantly to advancements in real-world autonomous driving research.

While we have aimed to achieve maximum comprehensiveness, the expansive nature of this topic makes it challenging to encompass all noteworthy works. Nonetheless, by illustrating the current state of small-scale cars, we hope to offer a distinctive perspective to the community, which would generate more discussions and ideas leading to a brighter future of autonomous driving with small-scale cars.

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