

Motion Planning for Autonomous Driving: The State of the Art and Perspectives

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Abstract—Thanks to the augmented convenience, safety advantages, and potential commercial value, Intelligent vehicles (IVs) have attracted wide attention throughout the world. Although a few of autonomous driving unicorns assert that IVs will be commercially deployable by 2025, their implementation is still restricted to small-scale validation due to various issues, among which precise computation of control commands or trajectories by planning methods remains a prerequisite for IVs. This paper aims to review state-of-the-art planning methods, including pipeline planning and end-to-end planning methods. In terms of pipeline methods, a survey of selecting algorithms is provided along with a discussion of the expansion and optimization mechanisms, whereas in end-to-end methods, the training approaches and verification scenarios of driving tasks are points of concern. Experimental platforms are reviewed to facilitate readers in selecting suitable training and validation methods. Finally, the current challenges and future directions are discussed. The side-by-side comparison presented in this survey not only helps to gain insights into the strengths and limitations of the reviewed methods but also assists with system-level design choices.

Index Terms—Pipeline planning, end-to-end planning, imitation learning, reinforcement learning, parallel learning.

I. INTRODUCTION

INTELLIGENT vehicles (IVs) have gained considerable attention from government, industry, academia, and the

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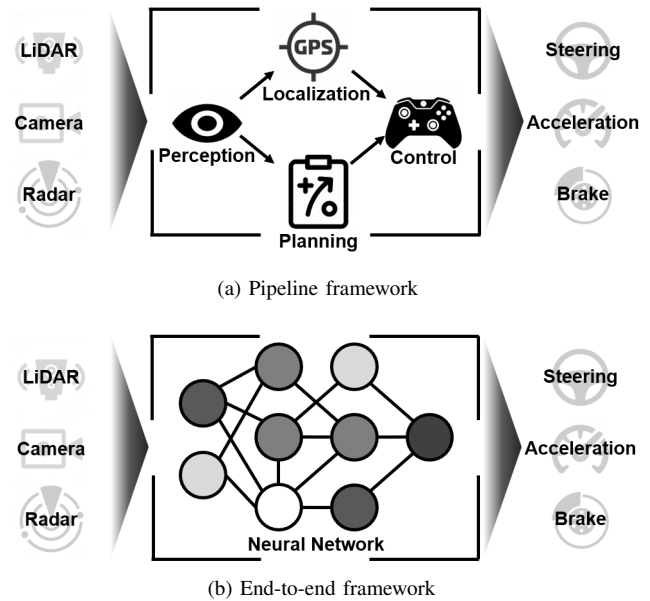


Fig. 1. Modular and end-to-end frameworks surveyed in [1]. The modular framework for autonomous driving consists of many interconnected modules, while the end-to-end method treats the entire framework as one learnable learning task.

general public due to their potential to revolutionize transportation, facilitated by advances in artificial intelligence and computer hardware [2]. The deployment of IVs in the environmental landscape has the great potential to reduce road accidents and traffic congestion so as to improve our mobility in overcrowded megacities [3]. Although phenomenal contributions achieved by plenty of the leading names in this area, IVs are still out of reach except in limited trial programs due to key concerns about their reliability and safety. In order to achieve a higher level of awareness of the surrounding environments, and increased safety, efficiency, and capabilities, IVs are always equipped with different types of sensors. Despite multifarious sensors, IVs are constrained by the ability to inadequately detecting in adverse scenarios. Thus ensuring the safety, robustness, and generalization of planning methods is a pivotal problem for the implementation of autonomous driving [4].

This paper presents a comprehensive analysis of the general planning method for autonomous driving. Generally speaking, the planning methods for autonomous driving can be classified into two categories, i.e., pipeline and end-to-end.

The pipeline planning method, also known as the rule-based planning approach, is a well-established method and

extensively adopted by the industry. As shown in Fig. 1a, this method is a subset of the pipeline framework and needs to be coupled with other methods to accomplish autonomous driving tasks, such as perception [5], localization, and control. As a major advantage, the pipeline framework is interpretable, the defective module can be identified when a malfunction or unexpected system behavior occurs. To limit the scope of Section-II, we only concentrate on aspects of the planning method within the pipeline framework. The pipeline planning method consists of two primary components: global route planning generating a road-level path from the origin to the destination, and local behavior and (or) trajectory planning generating a short-term trajectory. Although the pipeline planning method is widely used in industry, the restriction of the method is that it requires a large volume of computation resources and many manual heuristic functions [6]. In this study, we focus on the expansion and optimization mechanisms of the pipeline planning method.

The end-to-end planning method, also known as the learning-based approach, is a new kind of approach and has become a tendency in autonomous vehicle research. In this method, the entire driving pipeline is regarded as a single machine-learning task which transfers raw perception data to control commands. The driving model can learn knowledge via imitation learning, explore driving policy via reinforcement learning, and continuously self-optimize via parallel learning. Despite its appealing concept, it is difficult or even impossible to find out the reasons when the model misbehaves. In this case, our study concentrates on the network structure, training technique, and deployment tasks of the end-to-end model.

In Section-II, we begin with reviewing pipeline planning methods, including global route planning and local behavior/trajectory planning, where we especially discuss the expansion and optimization mechanisms. The reviewed end-to-end planning methods, including imitation learning, reinforcement learning, and parallel learning are listed in Section-III. The network architect, generalizability and robustness, and validation & verification methods are explored in detail. In addition, large datasets, simulation platforms, and physical platforms play auxiliary roles in the development of autonomous driving with higher levels of intelligence and mobility, thus, we summarize other contents of autonomous driving in Section-IV, including the dataset, simulation platforms, and physical platforms. Finally, we review the current challenges and future directions of autonomous driving in Section-V.

The contributions of this survey are outlined as follows:

- This survey presents the first comprehensive review of all planning methods in IVs, encompassing both pipeline planning and end-to-end planning approaches.
- This survey provides a thorough analysis and summary of the latest datasets, simulation platforms, and semi-open real-world testing scenarios.
- This survey gives a summary of the current open challenges and lays out future research directions.

II. PIPELINE PLANNING METHODS

The pipeline method also named the modular approach, is widely used by the industry and is nowadays considered the

conventional approach. The pipeline system stems from architectures that evolved primarily for autonomous mobile robots and that are built of self-contained but inter-connected modules such as perception, localization, planning, and control.

The pipeline method planning framework is responsible for calculating a sequence of trajectory points for the low-level controller of the ego-vehicle to track, which typically contains three functions, namely global route planning, local behavior planning, and local trajectory planning [7], [8]. Global route planning provides a road-level path from the start point to the end point on a global map.

“Local” stands for the resultant trajectory which is short in spatial or temporal range; otherwise, the ego-vehicle cannot react to risks beyond the sensor ranges, local behavior planning decides a driving action type (e.g., car-following, nudge, side pass, yield, and overtake) for the next several seconds while local trajectory planning generates a short-term trajectory based on the decided behavior type.

Actually, the boundary between local behavior planning and local trajectory planning is rather blurred [7], e.g., some behavior planners do more than just identify the behavior type. For the convenience of understanding, this paper does not distinguish between the two functions strictly and the related methods are simply regarded as trajectory planning methods. Thus, this section categorizes the related algorithms into two functions: global route planning and local behavior/trajectory planning.

A. Global Route Planning

Global route planning is responsible for finding the best road-level path in a road network, which is presented as a directed graph containing millions of edges and nodes. A route planner searches in the directed graph to find the minimal-cost sequence that links the starting and destination nodes. Herein, the cost is defined based on the query time, preprocessing complexity, memory occupancy, and solution robustness considered. Edsger Wybe Dijkstra is a pioneer in this field and innovatively proposes the Dijkstra algorithm [9] named after him. Lotfi et al. [10] construct a Dijkstra-based intelligent scheduling framework that computes the optimal scheduling for each agent, including maximum speed, minimum movement, and minimum consumption cost. A-star algorithm [11] is another famous algorithm in road-level navigation tasks, it leverages the advantages of the heuristic function to streamline research space. All of these algorithms substantially alleviate the problem of transportation efficiency and garnered significant attention in the field of intelligent transportation systems.

B. Local Behavior/Trajectory Planning

Local behavior planning and local trajectory planning functions work together to compute a safe, comfortable and continuous local trajectory based on the identified global route from route planning. Since the resultant trajectory is local, the two functions have to be implemented in a receding-horizon way unless the global destination is not far away [12]. It deserves to emphasize that the output of the two functions should be

a trajectory rather than a path [13], [14], and the trajectory interacts with other dynamic traffic participants, otherwise, extra efforts are needed for the ego vehicle to evade the moving obstacles in the environment.

Nominally, local planning is done by solving an optimal control problem (OCP), which minimizes a predefined cost function with multiple types of hard or soft constraints satisfied [15], [16]. The solution to the OCP is presented as time-continuous control and state profiles, wherein the desired trajectory is reflected by a part of the state profiles. Since the analytical solution to such an OCP is generally not available, two types of operations are needed to construct a trajectory. Concretely, local planning is divided into three parts, the first type of operation is to identify a sequence of state grids, the second type is to generate primitives between adjacent state grids, and The third is an organic combination of the first two.

1) *State grid identification*: State grid identification can be done by search, selection, optimization, or potential minimization. Search-based methods abstract the continuous state space related to the aforementioned OCP into a graph and find a link of states there. Prevalent search-based methods include A* search [17] and dynamic programming (DP) [17], [18]. Many advanced applications of these algorithms have pushed its influence to the top of the heap, such as Hybrid A* [19], Bidirection A*, Semi-optimization A* [20], and LQG framework [18]. Selection-based methods decide the state grids in the next one or several steps by seeking the candidate with the optimal cost function. Greedy selection [21] and Markov decision process (MDP) series methods typically [22], [23] fall into this category.

An optimization-based method discretizes the original OCP into a mathematical program (MP), the solution of which are high-resolution state grids [24], [25]. MP solvers are further classified as gradient-based and non-gradient-based ones; gradient-based solvers typically solve nonlinear programs [16], quadratic programs [24], [26], [27], quadratically constrained quadratic programs [28] and mix-integer programs; non-gradient-based solvers are typically represented by metaheuristics [29]. Multiple previous methods could be combined to provide a coarse-to-fine local behavior/motion planning strategy.

2) *Primitive generation*: Primitive generation commonly manifests as closed-form rules, simulation, interpolation, and optimization. Closed-form rules stand for methods that compute primitives by analytical methods with closed-form solutions. Typical methods include the Dubins/Reeds-Shepp curves [30], [31], polynomials [21], and theoretical optimal control methods [32], [33]. Simulation-based methods generate trajectory/path primitives by forwarding simulation, which runs fast because it has no degree of freedom [17]. Interpolation-based methods are represented by splines or parameterized polynomials [31]. Optimization-based methods solve a small-scale OCP numerically to connect two state grids [34], [35].

3) *Other Approaches*: State grid identification and primitive generation are two fundamental operations to construct a trajectory. Both operations may be organized in various ways. For example, Kuwata et al. [36] integrate both operations in an iterative loop; HU et al. [34] build a graph of primitives

offline before online state grid identification; Fan et al. [26] identify the state grids before generating connective primitives. If a planner only finds a path rather than a trajectory, then a time course should be attached to the planned path as a post-processing step [35]. This strategy, denoted as path velocity decomposition (PVD), has been commonly used because it converts a 3D problem into two 2D ones, which largely facilitates the solution process. Conversely, non-PVD methods directly plan trajectories, which has the underlying merit to improve the solution optimality [18], [37]–[39].

Recent studies in this research domain include how to develop specific planners that fit specific scenarios/tasks particularly [12], [38], and how to plan safe trajectories with imperfect upstream/downstream modules [38]. The past decades have seen increasingly rapid progress in the autonomous driving field. In addition to the advances in computing hardware, this rapid progress has been enabled by major theoretical progress in the computational aspects of mobile robot motion planning theory. Research efforts have undoubtedly been spurred by the improved utilization and safety of road networks that intelligent vehicles would provide.

III. END-TO-END PLANNING METHODS

End-to-end stands for the direct mapping from raw sensor data into trajectory points or control signals. Because of its ability to extract task-specific policies, it has been utilized with great success in a variety of fields. Compared with the pipeline method, there is no external gap between the perception and control modules and seldom human-customized heuristics are embedded, so the end-to-end method deals with vehicle-environment interactions more efficiently [40]. End-to-end has a higher ceiling, with the potential to achieve expert performance in the autonomous driving field. In this section, we divide the end-to-end method into three categories: imitation learning, reinforcement learning, and parallel learning.

A. Imitation Learning

Imitation learning (IL) refers to the agent learning policy based on expert trajectory, which generally provides expert decisions and control information [41]. Each expert trajectory contains a sequence of states and actions, and all “state-action” pairs are extracted to construct datasets. In the IL task, the model leverages constructed dataset to learn the latent relationship between state and action, the state stands for a feature and the action demonstrates labels. Thus, the specific objective of IL is to appraise the most fitness mapping between state and action, so that the agent achieves the expert trajectories as much as possible. Table I presents all famous imitation learning methods reviewed in this part.

There are three widely used training methods [60], first manifests as a negative method, named behavioral cloning (BC); The second builds on BC, named direct policy learning (DPL); The last is a task-dependent method, named inverse reinforcement learning (IRL) method.

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

Article	Category	Input	Output	Implement Tasks	Auxiliary Method	Dataset
Bojarski et al. [42]	BC	monocular image	steering angle	lane Keeping	CNN is the only component of end-to-end model	physical & simulate platform
Codevilla et al. [43]	BC	monocular image	control information	simulation navigation task	High-level commands as a switch to select the branch	Carla
Chen et al. [44]	BC	monocular image	control information	simulation navigation task	Affordance is used to predict control actions	TORCS Dataset & KITTI
Sauer et al. [45]	BC	monocular video & directional input	control information	physical navigation task	Conditional affordance is trained to calculate intermediate representations	Carla
Zeng et al. [46]	BC	Lidar data & HD Map	trajectory, scenario representation	physical navigation task	The intermediate representation is used to improve the model's interpretability	physical dataset collected in North America
Sadat et al. [47]	BC	Lidar data & HD Map	trajectory, scenario representation	physical navigation task	A joint system with interpretable intermediate representations for interpretable planner	physical dataset collected in North America
Ross et al. [48]	DPL	monocular image	control information	autonomous racing competition	An iterative algorithm is proposed to guarantee the performance in corner cases	3D racing simulator
Zhang et al. [49]	DPL	monocular image	control information	autonomous racing competition	Embedded query-efficient model to reduce the requirement for expert trajectories	racing car simulator
Yan et al. [50]	DPL	LiDAR, ego-vehicle speed, Sub-goal	control information	physical & simulation navigation task	The novice and the expert policy is fused to control the robot	physical and simulate platform
Li et al. [51]	DPL	monocular image & sub-goal	waypoint, control information	autonomous racing	A reward-based online method learns from multiple experts	Sim4CV
Ohn-Bar et al. [52]	IRL	monocular image	control information	simulation navigation task	Scenario context is embedded into the policy learning network	Carla
Levine et al. [53]	IRL	BEV image	control information	keep the lane, change lanes & takeover	The gaussian algorithm is used to learn the relevance of features in expert trajectories.	Highway driving simulator
Brown et al. [54]	IRL	monocular image	control information	keep the lane, change lanes & takeover	The high-confidence upper bounds on the α -worst-case are embedded into the policy network.	Highway driving simulator
Palan et al. [55]	IRL	monocular image	control information	keep the lane, change lanes & takeover	A globally normalized reward function is constructed.	Lunar lander simulator
Ziebart et al. [56]	IRL	Road network, Sub-goal, & GPS Data	control information	long range autonomous navigation task	A probabilistic approach is proposed for maximum entropy	Driver route modeling
Lee et al. [57]	IRL	monocular image	control information, costmap	keep the lane, change lanes & takeover	The query generation process is used to improve the generalization	NGSIM & Carla
Ho et al. [58]	IRL	monocular image	control information	keep the lane, change lanes & takeover	GAN is integrated into the end-to-end model	Carla
Phan et al. [59]	IRL	BEV image, HD map, obstacle information	Control information	physical navigation task	A three-step IRL planner is proposed	physical dataset from the Las Vegas Strip

1) *Behavioral Cloning*: Behavioral Cloning (BC) manifests as the primary method of IL in autonomous driving [42], [61]. The agent leverages the state-action pairs from the expert to the training model and then replicates the strategy using a classifier/regressor. BC is a passive method, where the objective is to learn the target strategy by passively observing the complete execution of commands, however, this requires the premise that the state-action pairs in all trajectories are independent. Bojarski et al. [42] construct a pioneering framework for BC, which trains a convolutional neural network to only compute steering from a front-view monocular camera. This method exclusively outputs lateral control while

ignoring longitudinal commands, rendering it can only be implemented in a limited number of uncomplicated scenarios. Codevilla et al. [43] proposed a famous IL model, named conditional imitation learning (CIL), which contains both lateral and longitudinal control, as shown in Fig. 2. Monocular images, velocity measurement of ego-vehicle, and high-level commands (straight, left, right and lane following) are used as input to CIL, and both predicted longitude and latitude control commands as output. Each command acts as a switch to select a specialized sub-module. CIL is a milestone for the CL method in autonomous driving and demonstrates that the convolutional neural network (CNN) can learn to perform lane

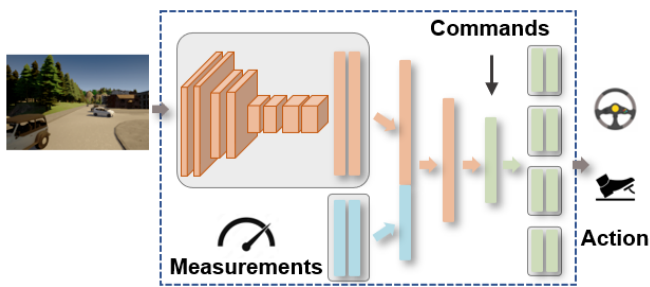


Fig. 2. The model proposed in [43]. Measurements stand for the velocity of ego-vehicle. The high-level command, including straight, left, right, and lane following. Actions are control signals including steering, accretion, and brake.

and road tracking tasks autonomously.

Based on CIL [43], many researchers include additional information such as global route, location information, or point cloud in the input stage [62]–[64]. These methods demonstrate strong generalization and robustness in various conditions, because of sufficient perception data input.

Because of its novel structure, IL methods exclude uncertainty estimation among different sub-systems and lead to fewer feedback milliseconds. However, this characteristic leads to a significant drawback, lack of interpretability, which does not provide sufficient reasons to explain the decisions. Many researchers try to address this pain point by inserting the intermediate representation layer. Chen et al. [44] propose a novel paradigm, named direct perception method, to predict an affordance for urban autonomous driving scenarios. The affordance represents a BEV format that clearly displays features about the surrounding environment and then is fed to a low-level controller to generate steering and acceleration. Sauer et al. [45] further propose an advanced direct perception model, which leverages video and high-level commands to intermediate representations and computes control signals as output. Compared with [44], this model can handle complex scenarios in urban traffic scenarios. Urtaun and her team also propose two interpretable end-to-end planners [46], [47], both planners leverage raw LiDAR data and High-Definition Map (HD Map) to predict safe trajectories and intermediate representations, which are utilized to present how policy responds to surrounding scenarios.

The main feature of the BC method is that only experts can generate training examples, which directly leads to the training set being a subset of the states accessed during the execution of the learned policy [65]. Therefore, when the dataset is biased or overfitted, the method is limited to generalize. Moreover, when the agent is guided to an unknown state, it is hard to learn the correct recovery behavior.

2) *Direct Policy Learning*: Direct Policy Learning (DPL), a training method based on BC, evaluates the current policy and then obtains more suitable training data for self-optimization. Compared with BC, the main advantage of DPL leverages expert trajectories to instruct the agent how to recover from current errors [60]. In this way, DPL alleviates the limitation of BC due to insufficient data. In this section, we summarize a series of DPL methods.

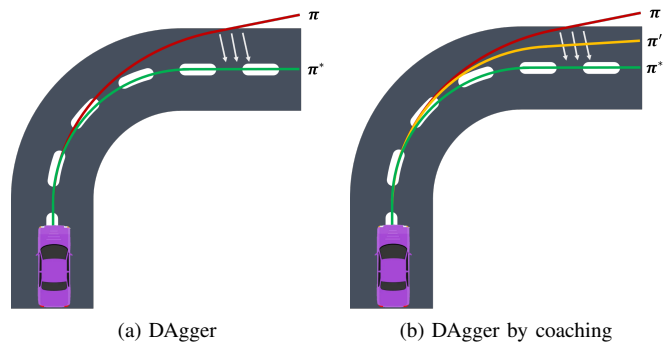


Fig. 3. The DAgger method [48] for Autonomous Driving Navigation Task.

Ross et al. [48] construct a classical online IL method named Dataset Aggregation (DAgger) method. This is an active method based on the Follow-the-Leader algorithm [60], each validation iteration is an online learning example. The method modifies the main classifier or regressor on all state–action pairs experienced by the agent. DAgger is a novel solution for sequential prediction problems, however, its learning efficiency might be suppressed by the far distance between policy space and learning space. In reply, He et al. [66] propose a DAgger by coaching algorithm which employs a coach to demonstrate easy-to-learn policies for the learner and the demonstrated policies gradually converge to label. To better instruct the agent, the coach establishes a compromised policy which is not much worse than a ground truth control signal and much better than novice predicted action. As shown in Fig. 3, π is the predicted command, π^* shows the expert trajectory, and π' presents the compromised trajectory. π' is much easier than π^* for agent to learn sub-optimal policy in each iteration. The policy is asymptotically optimal.

Other researchers also point out some drawbacks of DAgger methods [48], [66]: inefficient query, inaccurate data collector, and poor generalization. In reply, Zhang et al. [49] propose the SafeDAgger algorithm, which intends to improve the query efficiency of DAgger and can further reduce the dependence on label accuracy. Hoque et al. [67] propose a ThriftyDAgger model, which integrates human feedback on corner cases, Yan et al. [50] propose a novel DPL training scheme for navigation tasks in mapless scenarios, both of them improve the generalization and robustness of the model.

DAgger-based methods reduce dataset dependency and improve learning efficiency, however, these methods cannot distinguish between good or bad expert trajectories and ignore the learning opportunity from unfitness behaviors. In reply, Li et al. [51] propose the observational imitation learning (OIL) method, which predicts the control commands from the monocular image and embeds waypoints as intermediate representations. OIL manifests as an online learning policy based on a reward function, it could learn from multi-experts and abandon the wrong policies.

To fine-tune the agent policy in perception-to-action methods, Ohn-Bar et al. [52] propose a method for optimizing situational driving policies which effectively captures reasoning in different scenarios, shown in Fig. 4. The training policy is

divided into three parts. First, the model learns sub-optimal policies by the BC method. Second, context embedding is trained to learn scenario features. Third, refined the integrated model by online interaction with the simulation and collect better data by a DAgger-based method.

DPL is an iterative online learning policy that alleviates the requirements for the volume and distribution of dataset, while facilitating the continuous improvement of policies by effectively eliminating incorrect ones.

3) *Inverse Reinforcement Learning*: Inverse reinforcement learning (IRL) is designed to circumvent the drawbacks of the aforementioned methods by inferring the latent reasons between input and output. Similar to the prior methods, IRL needs to collect a set of expert trajectories at the beginning. However, instead of simply learning a state-action mapping, these expert trajectories are first inferred and then the behavioral policy is optimized based on the elaborate reward function. IRL method can be classified into three distinct categories, max-margin methods, Bayesian methods, and maximum entropy methods.

The max-margin method leverages expert trajectories to evaluate a reward function that maximizes the margin between the optimal policy and estimates sub-optimal policies. these methods represent reward functions with a group of features utilizing a linear combination algorithm, where all features are considered independent

Andrew Wu [68] is a pioneer in this field, he introduces the first max-margin IRL method, which puts forward three algorithms for computing the refined reward function. Furthermore, Pieter et al. [69] devise an optimized algorithm based on [68], which assumes that an expert reward function can be expressed as a manually crafted linear combination of known features, with the objective of uncovering the latent relationships between weights and features.

The limitation of prior methods is that the quality and distribution of the expert trajectories sets an upper bound on the performance of the method. In reply, Umar et al. [70] propose a game-theoretic-based IRL method named multiplicative weights for apprenticeship learning, it has the capability to import prior policy to the agent about the weight of each feature and leverages a linear programming algorithm to modify the reward function so that its policy is stationary.

In addition, Phan-Minh et al. [59] propose an interpretable planning system, as shown in Fig. 5. The trajectory generation module leverages perception information to compute a set of

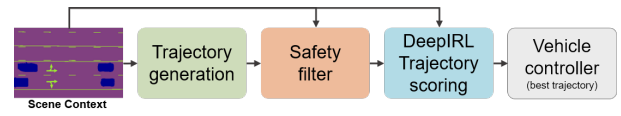


Fig. 5. The system proposed in [59] is divided into three stages: trajectory generation, safety filtering, and trajectory scoring.

future trajectories. The safety filter is used to guarantee basic safety with an interpretable method. DeepIRL trajectory scoring the predicted trajectories, which is the core contribution of this system. Furthermore, [71] and [72] propose preference-inference formulation, users can choose actions according to their personal preferences, which indeed improves the performance of the model.

The second part of IRL is Bayesian methods, which often leverage the optimized trajectory or the prior distribution of the reward to maximize the posterior distribution of the reward. The first Bayesian IRL is proposed by Ramachandran et al. [73], which references the IRL model from a Bayesian perspective and infers a posterior distribution of the estimated reward function from a prior distribution. Levine et al. [53] integrate a kernel function into the Bayesian IRL model [73] to improve the accuracy of estimating reward and promote the performance in unseen driving.

Furthermore, Brown et al. [54] construct a sampling-based Bayesian IRL model, which utilizes expert trajectories to calculate practical high-confidence upper bounds on the α -worst-case difference in expected return under the unseen scenarios without a reward function. Palan et al. [55] propose DemPref model, which utilizes the expert trajectory to learn a coarse reward function, the trajectory is used to ground the (active) query generation process, to improve the quality of the generated queries. DemPref alleviates the efficiency problems faced by standard preference-based learning methods and does not exclusively depend on high-quality expert trajectories.

The third part of IRL is the maximum entropy method, which is defined by using maximum entropy in the optimization routine to estimate the reward function. Compared with the previous IRL method, Maximum entropy methods are preferable for continuous spaces and have the potential ability to address the sub-optimal impact of expert trajectories. The first Maximum Entropy IRL model is proposed by Ziebart [56], which leverages the same method as [68] and could alleviate both noises and imperfect behavior in the expert trajectory. The agent attempts to optimize the reward function under supervision by linearly mapping features to rewards.

And then, many researchers [57], [58], [74] implement the maximum entropy IRL to physical end-to-end autonomous driving. Among them, [58] propose Generative Adversarial Imitation Learning (GAIL), which has become a classical algorithm in this field. GAIL leverages a generative adversarial network (GAN) to generate the distribution of expert trajectories with a model-free method in order to alleviate the problem of state drift caused by insufficient datasets. Because of sufficient reconstruction expert trajectories and competitive policies, GAIL achieves performance comparable to that of human drivers in specific scenarios. Based on [58], many

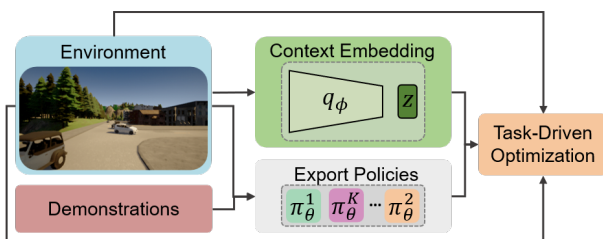


Fig. 4. Training policies propose in [52]. Export policies learn sub-optimal policy. Context Embedding is trained to learn scenarios. Both Context Embedding and Export Policies are fine-tuning in Task-Driven Optimization by Online method.

works have been proposed, such as InfoGAIL [75], Directed-InfoGAIL [76], Co-GAIL [77], all of them achieve competitive results in their implement fields.

IRL provides several excellent works for autonomous driving, however, like the aforementioned methods, it also has long tail problems in corner cases. How to effectively improve the robustness and interpretability of IRL is also a future direction.

B. Reinforcement Learning

IL methods require large amounts of manually labeled data, and diverse drivers may arrive at entirely distinct decisions when presented with identical situations, which leads to uncertainty quandaries during training. In order to obviate the hunger for labeled data, some researchers have endeavored to utilize reinforcement learning (RL) algorithms for autonomous decision planning. The agent can obtain some rewards by interacting with the environment. The objective of RL is to optimize cumulative numerical rewards via trial-and-error. By consistently interacting with the environment, the agent gradually acquires knowledge of the optimal policy to attain the target endpoint.

With the advancement of artificial intelligence, deep reinforcement learning (DRL) integrates the feature-extracting capabilities of deep learning with the decision-making abilities of conventional reinforcement learning. This facilitates the resolution of dilemmas arising from high dimensionality state and extensive action space, and culminating in end-to-end autonomous driving from state input to action output. In this survey, we classify the main RL methods into four parts: Value-based Reinforcement Learning, Policy-based Reinforcement Learning, Hierarchical Reinforcement Learning (HRL), and Multi-Agent Reinforcement Learning (MARL), the reviewed methods are listed in Table II.

1) *Value-based Reinforcement Learning*: Value-based methods try to estimate the value of different actions in a given state and learn to assign a value to each action based on the expected reward that can be obtained by taking that action in that state. The agent learns to associate the rewards with the states and actions taken in the environment and leverages this information to make optimal decisions [78].

Among value-based methods, Q-Learning [79] stands out as the most prominent. The framework for implementing Q-Learning in end-to-end planning is illustrated in Fig. 6. Mnih et al. [80] propose the first deep learning method by a Q-learning based approach that learns directly from screenshots to control signals. Furthermore, Wolf et al. [81] introduce the Q-learning method into the intelligent vehicle field, they define five different driving maneuvers in the Gazebo simulator [82], and the vehicle chooses a corresponding maneuver based on the image information. For the purpose of alleviating the problem of poor stability with high-dimensional perception input. The Conditional DQN [83] method is proposed, which leverages a defuzzification algorithm to enhance the predictive stability of distinct motion commands. The proposed model achieves a performance comparable to human driving in specific scenarios

In order to perform high-level decision-making for IVs on specific scenarios, Alizadeh et al. [84] train a DQN agent

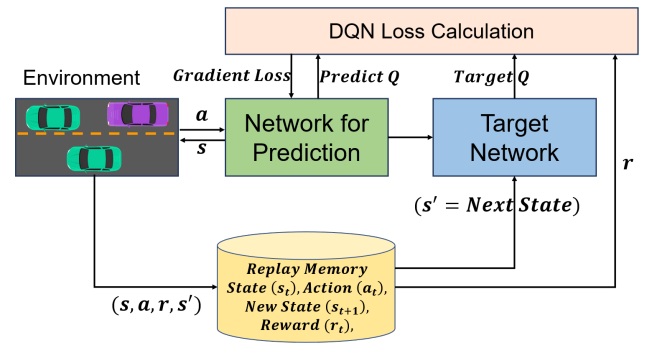


Fig. 6. The architecture of DQN-based end-to-end autonomous driving method.

combined with DNN which outputs two discrete actions. The safety and agility of the ego vehicle can be balanced on-the-go, indicating that the RL agent can learn an adaptive behavior. Furthermore, Ronecker et al. [85] propose a safer navigating method for IVs in highway scenarios by combining Deep Q-Networks from control theory. The proposed network is trained in simulation for central decision-making by proposing targets for a trajectory planner, which shows that the value-based RL can produce efficient and safe driving behavior in highway traffic scenarios.

The security of end-to-end autonomous driving also raises significant apprehension. Constrained Policy Optimization (CPO) [86] is a pioneering general-purpose policy exploit algorithm for constrained reinforcement learning with guarantees for near-constraint satisfaction at each iteration. Building on this, [87] and [88] present the Safety Gym benchmark suite and validate several constrained deep RL algorithms under constrained conditions. Li et al. [89] introduce a risk awareness algorithm into DRL frameworks to learn a risk-aware driving decision policy for lane-changing tasks with the minimum expected risk. Chow et al. [90] propose safe policy optimization algorithms that employ a Lyapunov-based approach [91] to address CMDP problems. Furthermore, Yang et al. [92] construct a model-free safe RL algorithm that integrates policy and neural barrier certificate learning in a stepwise state constraint scenario. Mo et al. [93] leverage Monte Carlo Tree Search to reduce unsafe behaviors on overtaking subtasks at highway scenarios.

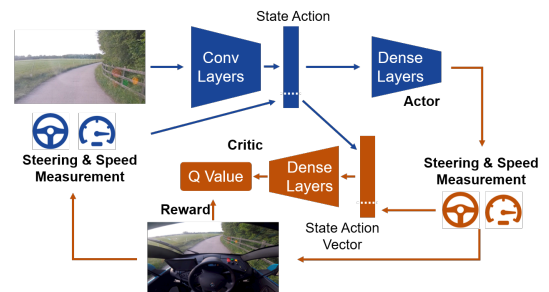


Fig. 7. The actor-critic algorithm used to learn a policy and value function for driving proposed in [94].

2) *Policy-based Reinforcement Learning*: The value-based approach is limited to providing discrete commands. However, autonomous driving is a continuous process, continuous commands within an uninterrupted span can be controlled at a fine-grained level. Therefore, the continuous approach is better for vehicle control. Policy-based methods hold the potential for high ceilings in high-dimensional action spaces with continuous control commands. These methods exhibit superior convergence and exploration than value-based methods.

The execution of RL on real-world IVs is a challenging assignment. Kendall et al. [94] implement the Deep Deterministic Policy Gradient (DDPG) [95] algorithm on an actual intelligent vehicle, performing all exploration and optimization on-board, as shown in Fig. 7. Monocular images are the only input, the agent learns the lane-following policy and achieves human-level performance in a 250m road test. This work marks the first application of implementing deep reinforcement learning on a full-sized autonomous vehicle. To further enhance driving safety and comfort, Wang et al. [96] introduce an innovative method for IVs based on the lane-change policy of human experts. This method can be executed on single or multiple vehicles, facilitating smooth lane changes without the need for V2X communication support.

To alleviate the challenge of autonomous driving on congested roads, Saxena et al. [97] employ the proximal policy optimization (PPO) algorithm [98] to learn a control policy in a continuous motion planning space. Their model implicitly simulates interaction with other vehicles to avoid collisions and enhance passenger comfort. Building on this work, Ye et al. [99] leverage PPO to learn an automated lane change policy on real highway scenarios. Taking the ego vehicle and its surrounding vehicle states as input, the agent learns to avoid collisions and to drive in a smooth manner. Several other studies [100], [101] have also demonstrated the efficacy of PPO-based RL algorithms in end-to-end autonomous driving policy learning

Training a policy from scratch in RL is frequently time-consuming and difficult. Combining RL with other methods such as imitation learning (IL) and curriculum learning may serve as a viable solution. Liang et al. [102] combine IL and DDPG together to alleviate the problem of low efficiency in exploring the continuous space, an adjustable gating mechanism is introduced to selectively activate four different control signals, which allows the model to be controlled by a central one. Tian et al. [103] leverage an RL method of learning from expert experience to implement trajectory-tracking tasks, which are trained in two steps, an IL method adopted in [63] and a continuous, deterministic, model-free RL algorithm to further fine-tune the method.

To address the learning efficiency limitations of RL methods, Huang et al. [104] devise a novel method, which incorporates human prior knowledge in RL methods. When confronted with the long-tail problem of autonomous driving, many researchers have turned their perspective to the exploitation of expert human experience. Wu et al. [105] propose a human guidance-based RL method which leverages a novel prioritized experience replay mechanism to improve the efficiency and performance of the RL algorithm in extreme scenarios, the

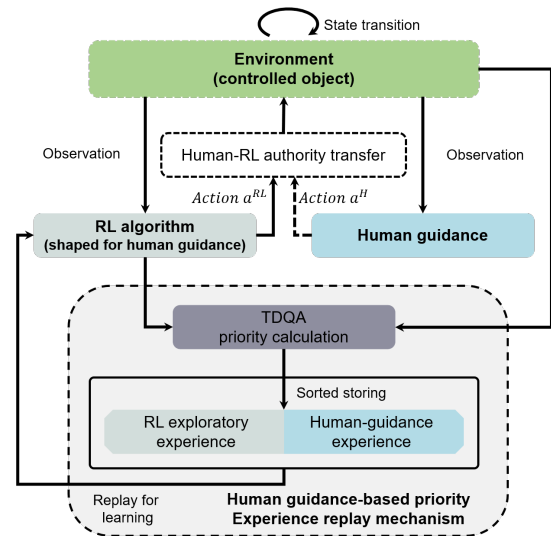


Fig. 8. Framework of the proposed human guidance-based RL algorithm [105].

framework of the proposed method is shown in Fig 8. This method is validated in two challenging autonomous driving tasks and achieves a competitive result.

3) *Hierarchical Reinforcement Learning*: RL methods have shown great promise in various domains, however, these methods are often criticized for difficult training. Especially in the autonomous driving field, non-stationary scenarios and high-dimensional input data cause intolerable training hours and resource usage [106]. Hierarchical reinforcement learning (HRL) decomposes the total problem into a hierarchy of subtasks, and each subtask has its own goal and policy. The subtasks are organized in a hierarchical manner, with higher-level subtasks providing context and guidance for lower-level ones. This hierarchical organization allows the agent to focus on smaller subproblems, reducing the complexity of the learning problem and making it more tractable.

Forcing the lane-changing task, Chen et al. [107] propose a two-level method. The high-level network learns policies for deciding whether to execute a lane change action, while the low-level network learns policies for executing the chosen commands. [108] and [109] also present a two-stage HRL methodology based on [107], where [108] needs to employ the pure pursuit to track the output trajectory points, and [109] integrates position, velocity and heading of ego-vehicle to further improve the performance of the low-level controller. All these proposed methods provide a promising solution for developing robust and safe autonomous driving systems.

The generalizability of HRL is a hot research point. Lu et al. [111] propose an HRL approach for autonomous decision-making and motion planning in complex dynamic traffic scenarios, as shown in Fig. 9. The approach consists of a high-level layer and a low-level planning layer, the high-level layer leverages a kernel-based least-squares policy iteration algorithm with uneven sampling and pooling strategy (USP-KLSPI) to solve the decision-making problems. Duan et al. [110] divide the whole navigation task into three models. The master policy network is trained to select the appropriate

driving task, this policy greatly enhances the generalizability and effectiveness of the model. For the purpose of further improving decision quality in complex scenarios, Cola-HRL [112] is presented based on [110], this method consists of three main components: a high-level planner, a low-level controller, and a continuous-lattice representation of the state space. Both the planner and controller use the state space to generate high-quality decisions. The results show that the Cola-HRL outperforms the other SOTA methods in most scenarios.

4) *Multi-Agent Reinforcement Learning*: In real scenarios, diverse traffic participants are commonly present, and their interactions can have a significant impact on the policy of each other [113]. In the single-agent system, the behavior of other participants is usually controlled based on pre-defined rules, and the predicted behavior of the agent may overfit the other participants, thus leading to a more deterministic policy other than in a multi-agent one [114]. Multi-Agent Reinforcement Learning (MARL) is designed to learn the decision-making policies of multiple agents in the environment. One popular modeling method for MARL is the decentralized partially observable Markov decision process (DEC-POMDP). However, the state space expands exponentially with the number of agents, making it more challenging and slow to train a multi-agent system (MAS) [115].

To reduce the impact of “the dimension explosion”, some effective learning schemes are proposed. Kaushik et al. [116] use a simple parameter-sharing DDPG to train the agent for two distinct tasks. By injecting the task into the observation space as a command, the same agent can act both competitively or cooperatively. Wang et al. [117] train autonomous agents in three scenarios: a ring network, a figure-of-eight network, and a mini city with various scenarios. Graph information sharing between each agent is integrated in the approach with PPO for continuous action generation, and vehicle communication is permitted within a certain range.

Although RL has been widely studied for lane-changing decision makings, those studies are mainly focused on a single-agent system. MARL methods provide a global perspective on multi-vehicle control. Zhou et al. [118] formulate the lane-changing decision-making of multiple autonomous vehicles coexisting with human-driven vehicles in a mixed-traffic highway scenario. Beyond simple tasks, MARL ap-

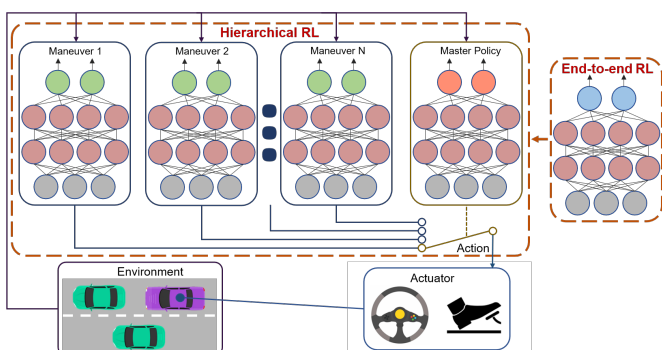


Fig. 9. The framework of hierarchical reinforcement learning (HRL) for self-driving decision-making proposed in [110].

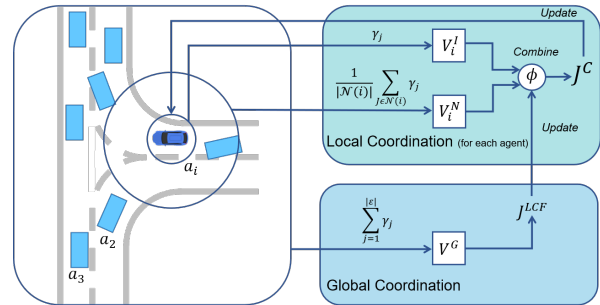


Fig. 10. The framework of the CoPO method proposed in [121]: the Local Coordination Factor (LCF) describes an agent’s preference of being selfish, cooperative, or competitive. A Local Coordination for each policy and a Global Coordination to update global LCF are both performed during training.

proaches have great potential to solve decision and planning problems in complex scenarios. Chen et al. [119] train agents to evade collisions in a time-critical merging highway scenario. The agents observe the locations and the velocities of the surrounding vehicles and then select corresponding actions.

Credit assignment is vital for policy learning in cooperative multi-agent scenarios. Han et al. [120] introduce an effective reward reallocating mechanism to motivate stable cooperation among IVs using a cooperative policy learning algorithm with Shapley value reward reallocation. The experimental results of this mechanism demonstrate significant improvement of the mean episode system reward in connected autonomous vehicles. Instead of reallocating rewards between agents, Peng et al. [121] incorporate the ring measure of social value orientation into the Self-Driven Particles (SDP) system which is a category of MAS. As each constituent agent in an SDP system is self-interested and the relationship between agents is constantly changing. The proposed method, Coordinated Policy Optimization (CoPO), performs local coordination between the agent and its neighbor vehicles within a certain distance, as shown in Fig 10. Experiments demonstrate that the proposed method outperforms MARL baselines across three main metrics: success rate, safety, and efficiency.

C. Parallel Learning

Planning methods in autonomous driving are constrained by several challenges. Pipeline planning methods couple numerous human-customized heuristics, which leads to inefficient computation and low generalization. Imitation learning (IL) methods require considerable volume and diverse distribution of expert trajectories, while reinforcement learning (RL) methods demand significant computational resources. Consequently, the presence of these limitations impedes the widespread implementation of autonomous driving.

In response to the various problems in planning methods, virtual-real interaction provides a proven solution [129]. Cyber-physical-systems (CPS) based intelligent control can facilitate interactions and integration between physical and cyberspaces but are not considering human and social factors in systems. In reply, many researchers have added social factors and artificial information to the CPS to form the cyber-physical-social systems (CPSS). In CPSS, the ‘C’ stands for

TABLE II
MAIN APPROACHES FOR MOTION PLANNING IN AUTONOMOUS DRIVING BASED ON DEEP REINFORCEMENT LEARNING.

Article	Method	Observation	Output	Scenario	Simulator
Wolf et al. [81]	Value-based, DQN	front cam	discrete Steering angle	lane keeping	Gazebo
Alizadeh et al. [84]	Value-based, DQN	relative distance & velocity value	trajectory points	lane change	Self-made environment
Ronecker et al. [85]	Value-based, DQN	relative distance & velocity value	trajectory points	lane change, highway strategy	Self-made environment
Li et al. [89]	Value-based, DQN	front cam	discrete lane change action	lane change & city strategy	CARLA
Mo et al. [93]	Value-based, DQN	front cam	discrete acceleration & lane change action	overtakeing & highway strategy	SUMO
Kendall et al. [94]	Policy-based, DDPG	front cam	continuous steering angle & speed setpoint	lane keeping	Unreal Engine 4
Wang et al. [96]	Policy-based, DDPG, DQN	front cam	discrete lane change action	lane change	Self-made environment
Saxen et al. [97]	Policy-based, PPO	lane based grid	continuous acceleration & steering angle	highway kinematic	Open source simulator
Ye et al. [99]	Policy-based, PPO	relative distance & velocity	discrete lane change action	lane change	SUMO
Liang et al. [102]	Policy-based, DDPG	front cam, Speed	continuous steering angle, acceleration, braking	navigation	CARLA
Tian et al. [103]	Policy-based, BC, DDPG	vehicle kinematic	continuous steering angle & vehicle speed	path tracking	Carsim/Simulink
Huang et al. [104]	Policy-based, BC, AC	BEV images	continuous target speed & discrete lane change action	unprotected left turn, roundabout	SMARTS
Wu et al. [105]	Policy-based, PHIL-TD3	BEV semantic graph	continuous steering angle & accelerating	left-turn, congestion	CARLA
Chen et al. [107]	HRL, AC, DQN	front cam	trajectory points	lane change	TORCS
Shi et al. [108]	HRL, DQN	relative distance & velocity	discrete lane change action & continuous acceleration	lane change	Self-made environment
Li et al. [109]	HRL, DQN	scenario state	discrete speed & steering angle	INTERACTION dataset	OpenAI GYM toolkit
Duan et al. [110]	HRL	policy-specific dynamics	discrete speed & steering increment	lane change	Highway environment
Lu et al. [111]	HRL, USP-KLSPI	14-DOF dynamics	discrete speed & steering action	lane merging	Matlab
Gao et al. [112]	HRL, DDPG, CNN	BEV perception data, HD-Map	continuous speed & steering angle	navigation	Real-world HD-maps
Kaushik et al. [116]	MARL, DDPG	continuous ego state, LIDAR	continuous speed & steering angle	highway navigation	TORCS
Wang et al. [117]	MARL, PPO	relative distance & velocity	continuous acceleration	road networks	Flow
Zhou et al. [118]	MARL, MA2C	relative distance & velocity	discrete acceleration	lane change action	Highway-env
Chen et al. [119]	MARL, MA2C	relative distance & velocity	discrete acceleration & lane change action	lane merging	Highway-env
Han et al. [120]	MARL, Reward Reallocation	front cam, LIDAR, vehicle kinematic	discrete lane change action	mixed traffic	CARLA
Peng et al [121]	MARL, CoPO	continuous ego state & LIDAR	continuous acceleration & steering angle values	multi scenarios	MetaDrive

two dimensions: the information system in the real world and the virtual artificial system defined by software. The 'P' refers to the traditional real system. The 'S' includes not only the human social system but also the artificial system based on the real world.

CPSS enables virtual and real systems to interact, feedback, and promote each other. The real system provides valuable datasets for the construction and calibration of the artificial system, while the artificial system directs and supports the operation of the real system, thus achieving self-evolution. Due to the advantages of virtual-real interaction, CPSS provides a

new verification method for end-to-end autonomous driving.

Based on CPSS, Fei-Yue Wang [122] proposes the concept of parallel system theory in 2004, as shown in Fig. 11, the core concept of which is the ACP method, an organic combination of artificial societies (A), computational experiments (C) and parallel execution (P). Over the past two decades, the research system of parallel system theory has been enriched and improved by a large number of implementations in practice [130], such as parallel intelligence [131], parallel control [132], [133], parallel management [134], parallel transportation [135], parallel driving [126], [136], parallel tracking [137],

parallel testing [128], parallel vision [125] and so on. The survey about the methods proposed in this section is shown in Table III-C.

In order to further expand the learning capabilities of neural networks, and to address the challenges of IL and RL, Li et al. [124] propose a basic framework for parallel learning based on the parallel system theory as shown in Fig. 12. In the action phase, parallel learning [124] follows the RL paradigm, employing state transfer to represent the movement of the model, learning from big data, and storing the learned policy in the state-transition function. Notably, parallel learning capitalizes on computational experimentation to refine the policy. Through feature extraction methods, small knowledge can be applied to specific scenarios or tasks, and used for parallel control. Here, “small” refers to specific and intelligent knowledge for the particular problem, rather than denoting the magnitude of knowledge.

An innovative training approach based on parallel learning [124] presents an alternative solution for problem-solving in fully end-to-end autonomous stacks. As shown in Fig. 13, Wang et al. [138] introduce a parallel driving framework, a unified approach for ITS and IVs. The framework directly bridges expert trajectories and control commands to compute the most optimal policy for specific scenarios. Plenty of expert trajectories are collected from real scenarios, and a neural network is employed to learn all these trajectories, inputs and outputs of this network are destination state and control signals. From the viewpoint of parallel learning, this is a self-labeling process, and the process significantly alleviates the data hunger of end-to-end methods.

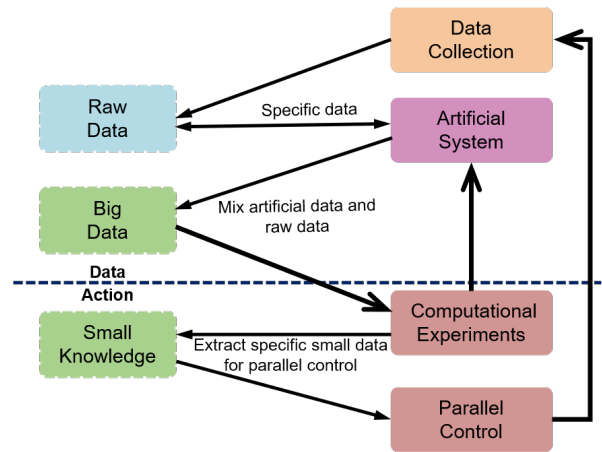


Fig. 12. The theoretical framework of parallel learning proposed in [124]. (The part above the dashed line focuses on big data preprocessing using artificial systems; the part beneath the dashed line focuses on computational experiments. The thin arrows represent either data generation or data learning; the thick arrows present interactions between data and actions.)

In order to handle the integrated data from the artificial system and computational experiment, a new theory is proposed, named parallel reinforcement learning (PRL), which combines the parallel learning and deep reinforcement learning approaches. Liu et al. [126] integrate digital quadruplets with

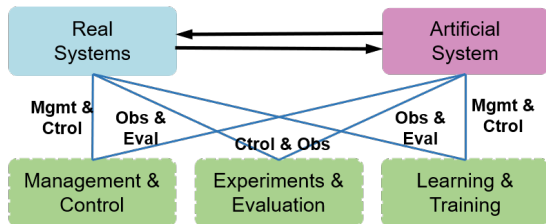


Fig. 11. The framework of parallel system theory proposed in [122].

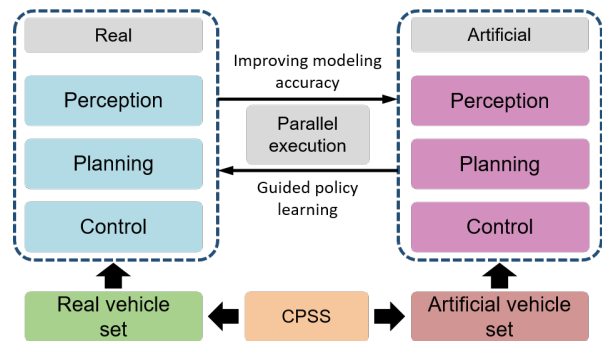


Fig. 13. The theoretical framework of the parallel driving proposed in [138].

TABLE III
THE SURVEY ABOUT THE PARALLEL SYSTEM THEORY AND ITS SOURCES AND DERIVED ALGORITHMS.

Method	Year	Detail
CPS	1990s	Proposing a multi-dimensional intelligent technology framework, based on big data, internet of things, and large computing, the organic integration and deep collaboration of computing, communication and control (3C).
CPSS [123]	2000	Integrating social signals and relationships into CPS, leveraging the human, data and information of the social network to break through the various limitations of the real world.
Parallel System Theory [122]	2004	Integrating artificial societies (A), computational experiments (C) and parallel execution (P), and provide effective tools for control and management of complex systems.
Parallel Learning [124]	2017	Proposing a new framework of machine learning theory, parallel learning, which incorporates and inherits many elements from various existing machine learning theories.
Parallel Vision [125]	2017	Introducing the parallel system theory into the computer vision area and constructing a novel research method for perception and understanding of complex driving scenarios.
Parallel Driving [126]	2019	Constructing an advanced and unified framework for autonomous driving that includes operation management, online condition management and emergency disengagement.
Parallel Planning [127]	2019	Constructing a deep planning method that integrates a convolutional neural network and a Long short-term memory module to improve the generalization and robustness of planning models in intelligent vehicles.
Parallel Testing [128]	2019	Proposing a closed-loop testing framework, which implements more challenging scenarios to accelerate evaluation and development of autonomous vehicles.

parallel driving. This framework defines the physical vehicle, the descriptive vehicle, the predictive vehicle, and the prescriptive vehicle. Based on the description of digital quadruplets, three virtual vehicles can be defined as three “guardian angels” for the physical vehicle, playing different roles to make the IVs safer and more reliable in complex scenarios.

Planning is one of the most significant components of autonomous driving. As a concrete implementation of parallel driving, Chen et al. [126], [138] propose a parallel planning framework for end-to-end planning, which constructs two customized approaches to solve emergency planning problems in specific scenarios. For the data-insufficient problem, parallel planning leverages artificial traffic scenarios to generate expert trajectories based on the pretrained knowledge from reality, as shown in Fig. 14. For the non-robustness problem, parallel planning utilizes a variational auto-encoder (VAE) and a generative adversarial network (GAN) to learn from virtual emergencies generated in artificial traffic scenes. For the learning inefficient problem, parallel planning learning policy from both virtual and real scenarios, and the final decision is determined by analysis of real observations. Parallel planning is able to make rational decisions without a heavy calculation burden when an emergency occurs.

The parallel system theory provides an effective tool for the control and management of complex systems, especially in the autonomous control field, parallel driving effectively alleviates the shortage of data, inefficient learning, and poor robustness for end-to-end planning models.

IV. EXPERIMENT PLATFORM

Testing IVs in real systems often comes with potentially fatal safety risks. Therefore, algorithms in autonomous driving are often evaluated in artificial systems with the utilization of open-source datasets and simulation platforms [154].

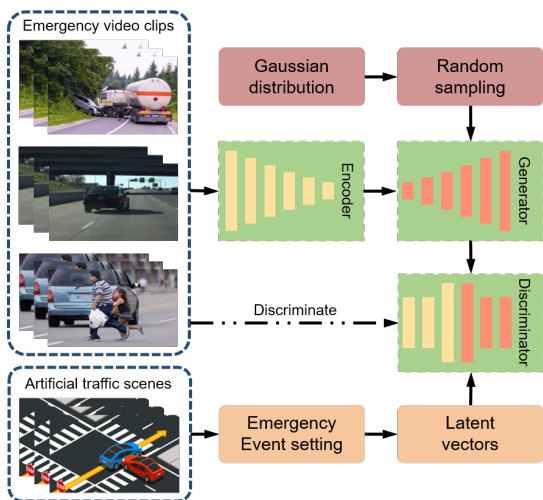


Fig. 14. Hybrid model of combining the variational auto-encoder (VAE) and the generative adversarial network (GAN) for predicting and generating potential emergency image sequences proposed in [127].

A. Dataset

The end-to-end method leverages widely available large-scale datasets of human driving to be trained to approximate human standards. Consequently, the training process requires a large amount of data from driving scenarios. The magnitude, abundance, and distribution of the dataset directly affect the safety, robustness, and generalization of the trained model. Though constructing and assembling novel datasets for IVs is time-consuming, numerous generic and influential datasets are available for research, such as Comma.ai [140], Bdd100K [146], A2D2 [147], Automine [148], DriverTruth [152] and Suprs [151], most of the famous dataset is shown in Table. IV.

KITTI [139] is a pioneer in this field and also the most famous autonomous driving dataset. Thanks to its good task scaling, KITTI now covers a wide range of basing perception tasks, such as object detection, sceneflow, depth estimation, tracking and so on.

Comma.ai [140] enriches the diversity of data by additionally collecting localization information and control signals, so it can be implemented for more tasks, for example, localization and planning.

BDD100K [146] and SODA10M [150] alleviate diversity and volume problems by constructing large-scale simulation scenarios, both of them collect several urban scenarios under various weather conditions in more than 31 cities, they also come with a rich set of labels: scene tagging, object bounding box, lane marking, drivable area, full-frame semantic and instance segmentation, multiple object tracking, and multiple objects tracking.

A2D2 [147] is a commercial-grade dataset that is well-suited for diverse perception tasks, bridging the gap between public datasets which are deficient in comprehensive vehicular information. Compared with previous datasets, it provides a 360° point cloud perception field by 5 LiDARs to enable full scene perception for autonomous driving.

The following dataset provides traffic scenarios that are distinct from structured scenarios. Automine [148] constructs the pioneering open-pit mine dataset for IVs, comprising 18 hours of transportation videos and localization information gathered from 6 open-pit mines. The distinctive features of open-pit mines, such as uneven and rough terrain, intense light, and copious dust, pose significant challenges. The Automine serves as a valuable resource to address the gaps in the open-pit mine dataset, and supports the advancement of autonomous mining technology. AI4MARS [149] proposes another interesting large-scale dataset, which consists of 35,000 semantic segmentation full images of the surface of Mars.

Currently, datasets cover almost all tasks of autonomous driving and play an increasingly vital role in facilitating the training and validation of intelligent vehicle algorithms. These supports establish the requisite groundwork to implement autonomous driving.

B. Simulation Platform

Testing autonomous driving algorithms in real-world scenarios is often accompanied by significant potential risks,

TABLE IV
DATASETS AND RELATED DESCRIPTIONS FOR THE AUTONOMOUS DRIVING DATASET.

Dataset	Year	Sensors	Scenarios
KITTI [139]	2013	4 cameras; 1 LiDAR	City; Countryside; Highway
Comma.ai [140]	2016	1 monocular camera; 1 point grey camera	Highway scenarios
Oxford RobotCar [141]	2016	6 Cameras; 3 LiDARS; Speed; GPS; INS	City; Contain weather changed
Mapillary Vistas [142]	2017	Image devices	Street Scenarios
nuScenes [143]	2019	6 Cameras; 5 Radars; 1 LiDAR	Street Scenarios
ApolloScape [144]	2019	2 Cameras; 2 LiDAR; GPS; IMU	Street Scenarios
Waymo Open Dataset [145]	2019	5 Cameras; 5LiDAR;	1150 Street Scenarios
BDD100K [146]	2020	1 Camera; GPS; IMU	Street scenarios in 4 cities
A2D2 [147]	2020	6 Cameras; 5 LiDAR; GPS; IMU	360° Street Scenarios
Automine [148]	2021	2 Cameras; 1 LiDAR; GPS; IMU	The first open-pit mine dataset
AI4MARS [149]	2021	2 Cameras	The first large-scale dataset in Mars
SODA10M [150]	2021	1 Camera	City Scenarios in 31 cities with all kinds of weathers
SUPS [151]	2022	6 Cameras; 1 LiDAR; GPS; IMU	Underground parking scenarios
DRIVERTRUTH [152]	2022	1 Camera; 1 LiDAR; GPS; IMU; Control signal	City Scenarios based-on CARLA
ROAD [153]	2023	1 Camera	Scenarios in [141] for road event detection

simulation testing shows a smart method to validate algorithms that can speed up testing due to its low cost and high safety.

Many autonomous driving simulation platforms have been developed with open-source code and protocols, which are available for the testing of algorithms in autonomous driving. SUMO [155], an open-source and microscopic traffic simulation platform, developed by the German Aerospace Center, offers a powerful validation platform for large-scale transportation algorithms. It is equipped with a well-designed interface that supports a broad range of data formats. Owing to its superior features, SUMO has been one of the earliest and most extensively utilized simulators. Moreover, Apollo [144] and Autoware [156] not only provide a simulation platform for validating algorithms but also equip open-source algorithms for each task, providing developers with a complete development-validation-deployment chain.

In the context of the ego-vehicle autonomous driving method, CARLA [157] offers a suitable answer. It is an open-source simulator for urban autonomous driving scenarios, which facilitates the development, training, and validation of the underlying urban autonomous driving system.

In the field of the multi-vehicle interaction method, TORCS [158] provides an open racing car simulator with over 50 diverse vehicle models and more than 20 racing tracks. Furthermore, it has the ability to race against 50 vehicles simultaneously, making it a valuable tool for research in this field. MetaDrive [159] proposes an open-source platform to support the research of generalizable reinforcement learning algorithms for machine autonomy. It is highly compositional and capable of generating an infinite number of diverse driving scenarios through both procedural generation and real data importing. The other simulation platforms and their related descriptions are shown in Table. V.

C. Physical Platform

With the increase in computer computing capabilities, simulation testing has become increasingly capable of meeting the testing requirements for various scenarios and has proven effective in solving the long-tail problem associated with such systems. However, pre-trained models used in a simulator typically require fine-tuning prior to implementation in the

real world. Moreover, while simulation testing can cover a wide range of scenarios, it can't account for all corner cases. Consequently, a professional and safe semi-open autonomous driving validation site is essential [[162].

Autonomous driving technology achieved significant development over the past few decades, and several countries adopt policies permitting the testing of robotic taxis on public roads. In the United States, Waymo is now permitted to test robotaxis on the streets of San Francisco from 2022. Nuro recently begins to deploy autonomous delivery vehicles in Arizona, California, and Texas. In England, Aurigo is conducting a trial of an autonomous shuttle at Birmingham airport. Wayve is authorized to test autonomous vehicles over long distances between five cities. In China, the commercialization of autonomous driving is rapidly progressing, with companies such as Apollo, Pony, and Momenta already implementing IVs in several cities. Additionally, Waytous is working on unmanned transport in unstructured and closed scenarios and has already provided driverless solutions for several open-pit mines.

V. CHALLENGES AND FUTURE DIRECTIONS

Considerable progress has been achieved in autonomous driving, as evidenced by its successful validation on semi-open roads in various cities. However, its complete commercial deployment is yet to be realized due to numerous obstacles and impending challenges that need to be surmounted.

A. Challenges

The challenges in IVs are summarised below:

Limitations of perception. Most autonomous driving frameworks heavily rely on perception results, but most sensors are limited by their inherent constraints. Vision sensors are susceptible to the effects of field of view and weather, and are less effective in back-lighting as well as strong light exposure. Perception results often suffer from partial perception problems, and thus potential dangers that are obscured by obstacles may be ignored. These drawbacks pose security challenges for autonomous driving.

Limitations of planning. Both pipeline and end-to-end planning have intrinsic limitations, and ensuring the production of high-quality outputs under uncertain and complex scenarios is an indispensable research objective.

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

Platform	Latest Version	Description
PTV Vissim	V2023	Traffic simulation platform focused on complex intersection design and active traffic management.
VTD	V2.2 (19.01)	Provides a complete bottom-up simulation platform, including ADAS and automation systems.
SUMO [155]	V1.15.0 (22.11)	Provides a purely microscopic traffic model that can be defined to customize each vehicle.
TORCS	V1.3.8 (17.03)	Support for running a large number of agents at the same time, allowing for scheduling functions in dense vehicle areas.
SVL Simulator [160]	V2021.3 (21.05)	Enables developers to simulate billions of miles and arbitrary corner cases to accelerate algorithm development and system integration.
V-Rep	V3.6.2 (19.01)	With a driving actions assessment function, which indicates the agent behavior based on the result.
CarMaker	V10.0 (21.10)	Specifically designed for the development and seamless testing of cars and light-duty vehicles in all development stages.
CARLA [157]	V0.9.13 (21.11)	Various city maps are provided for autonomous driving algorithms, as well as support for customized sensor types and weather conditions.
AriSim [161]	V1.8.1 (22.06)	The capability to quickly complete autonomous driving tests, and build various scenarios (urban, countryside, highway, field, etc.)
Apollo [144]	V8.0 (22.12)	Support for learning and validation of single and multi-vehicle autonomous driving algorithms on urban scenarios.
Autoware [156]	V1.11.0 (21.05)	An open-source autonomous driving platform, which include all component of autonomous function for intelligent vehicle.
Drive Constellation	V6.05 (22.10)	Provides a computing platform based on two different servers that can undertake large-scale vehicle data interaction services.
MetaDrive [159]	V0.2.6.0 (22.11)	A wide range of road segments are available, which can be customized to generate a variety of complex scenarios, more suitable for reinforcement learning.

Limitations of safety. Hacking incidents for autonomous driving systems are increasing, and even minor disruptions have the possibility to trigger significant deviations in decision-making. Therefore, the successful deployment of autonomous driving technology on a massive scale necessitates robust measures to counter adversarial attacks.

Limitations of datasets. Simulation datasets facilitate model training, and the well-trained model in simulation environments is often not directly transferable to reality. Therefore, bridging the gap between virtual and real data is an imperative research avenue [163].

B. Future Directions

Currently, planning methods are hard to handle all complex scenarios, and the models are also restricted by safety, generalization, and interpretability. Future research trends include:

- 1) Confronting the constraints of perception. Many researchers try to incorporate cognition into the perception layer. By leveraging human cognitive abilities, it is plausible to overcome autonomous driving challenges.
- 2) Tackling the problem of the uninterpretability of end-to-end methods. Many researchers enhance interpretability by generating interpretable intermediate representations in the latent layer. The exploration of employing these representations for end-to-end methods represents a research direction for IVs.
- 3) Managing the problem of hacker attacks on IVs, present defenses are proven inadequate against SOTA attacks, and the development of robust defense techniques against such attacks carries important research implications.
- 4) Facing challenges for decision-making in complex scenarios. Integrating human cognitive abilities into autonomous driving and a comprehensive understanding of scenario features is an effective way to overcome the present limitations.
- 5) Giving the challenges posed by the robustness and generalizability of planning methods, the well-trained large model in ChatCPT [164] shows surpassing human-level capability in solving complex problems. This holds true in the domain of autonomous driving as well, where a promising future direction concerns rationalizing the application of large models.
- 6) Confronting with the challenge of datasets migration from virtual to real, the description principle [165] of parallel system theory may serve as an efficacious solution. By coupling the two types of data using the description principle, a feedback loop is generated, which enables circular self-optimization.

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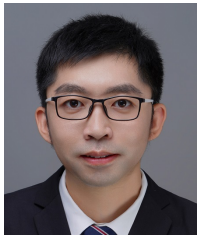
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