Proceedings of the 2023 International Conference on Machine Learning and Automation
DOI: 10.54254/2755-2721/33/20230265

Deep learning based visual perception and decision-making technology for autonomous vehicles

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Abstract. Along with the social fast developing and the scientific and technological advancement day by day, the automatic driving system has been widely used in many areas, so it has been a hotspot. Because of the constant progress of the deep learning technique, the vision environmental sensor technique and the behavior decision technique have obtained some inspiration. The paper introduces a new method for detecting target with human body, which is based on recurrent convolution neural networks. In recent years, we have seen a number of developments in the field of decision making, such as reinforcement learning, and the development of deep neural networks. This thesis mainly focuses on the research of VMI and decision algorithms, and gives a brief introduction to their further application in ATS. In this paper, some key techniques of vision sensing and behavior decision are discussed in detail. This paper analyses the merits and deficiencies of current study on environment sensing technique and behavior decision technique. Finally, this paper summarizes and forecasts the vision environmental awareness and behavior decision techniques.

Keywords: deep learning, reinforcement learning, autonomous driving, environment perception, computer vision, decision-making.

1. Introduction

Today, vehicles have become a necessary means of transport for people. Its convenience and efficiency have improved our lifestyle to a great extent. However, at the same time, it also creates problems such as traffic congestion and even traffic accidents, which are getting increasingly serious every year. With the progress of computer vision, AI and auto-control techniques, smart cars are born and get rapid development. The navigation system of intelligent vehicles mainly includes modules of Environment Perception, Localization and Mapping, Path Planning, Decision-Making, and Vehicle Control from the viewpoint of functional structure [1]. As shown in Figure 1.

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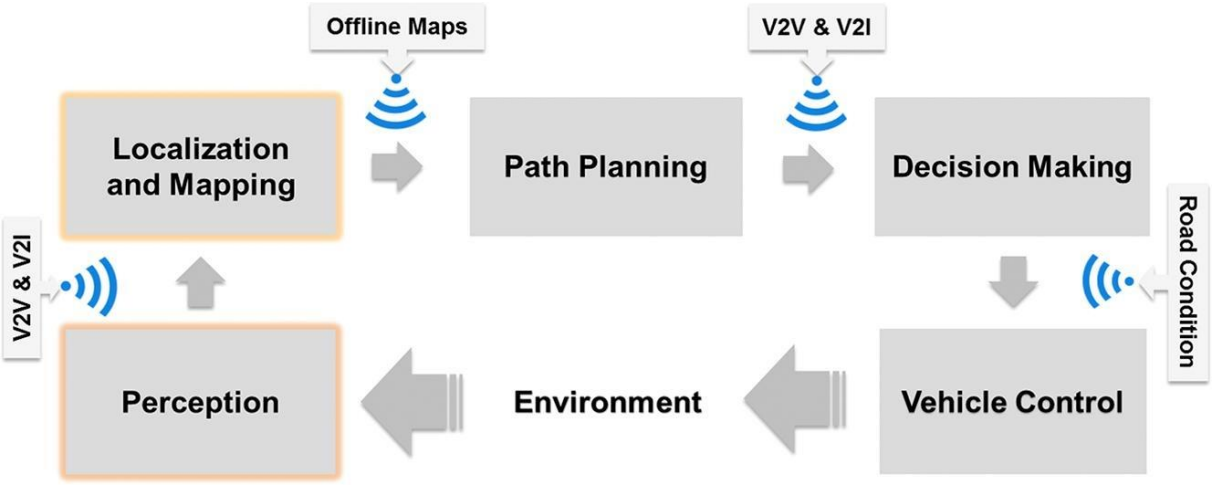

Figure 1. The Vehicle Navigation System [1].

Automatic driving environment perception technology refers to collecting, analyzing, and expressing the environmental information of vehicles, which is the foundation, as well as the key point and difficult point in automatic driving technology. Accurate and reliable environment perception technology guarantees the safety of automatic driving vehicles. Currently, there are four mainstream perception technologies: Machine Vision, LiDAR, Millimeter-Wave Radar, and Infrared Sensor [2]. Visual perception is based on the image information collected by the camera, which is processed using vision-related algorithms to recognize the surrounding environment. Since visual sensors have the characteristics of low cost and rich image information compared with other sensors such as lidar sensors or laser sensors, and with the dramatic improvement of digital image processing, computer vision, and deep learning technology, the visual perception technology based on deep learning has been widely used. Automatic driving decision-making and path planning technology means that it synthesizes the environment and the vehicle's information to control the vehicle's motion system. As a result, the intelligent vehicle can exhibit safe and logical driving behavior. Behavioral decision-making technology is a decision-making technology in a narrow sense, which makes a reasonable decision on the current vehicle behavior based on the information output from the environment perception, and determines the constraints of path planning based on different behaviors, and guides the path planning module to strategy appropriate routes, speeds, and other information, and sends them to the vehicle control module. The vehicle control layers takes instructions from the decision-making and path planning layers, and then regulates the response of vehicles to maintain the control precision and tracking the setting vehicle speed, path, and other information. The classical decision-making method is the Finite State Machine (FSM) method, which is divided into three structures: series, parallel, and mixed structure [3,4]. However, with the development of artificial intelligence, machine learning etc. learning algorithms are increasingly used in the environment sensing system and decision-making system of self-driving vehicles.

2. Visual environment perception technology

Vehicle, pedestrian, and obstacle detection is one of the core problems in visual environment perception for self-driving vehicles, and it is also a necessary condition for intelligent vehicles to truly realize autonomous driving. Before deep learning algorithms were widely used, due to the diversity of targets and backgrounds, human-designed algorithmic features often could not cope with the effects of light intensity, size, rotation and a series of factors, so the traditional object detection algorithms were not robust. In the past few years, deep learning technology has made significant advancements, resulting in excellent object detection performance.

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2.1. Recurrent-Convolutional Neural Network (R-CNN)

In 2014, for instance, Rose et al put forward an R-CNN target detecting algorithm [5]. The proposed method is one of the most widely used methods for object detection, as illustrated in Figure 2. The R-CNN model firstly identifies the candidate areas in an input image by Selective Search, and then extracts the characteristic map by means of the convolution neural network. The characteristic map is then input into the Support Vector Machine (SVM), which is trained by Chacra and others, with lots of tagged images. Although R-CNN is superior to conventional approaches in detecting performance, there are many issues such as time consuming and complex training and detecting.

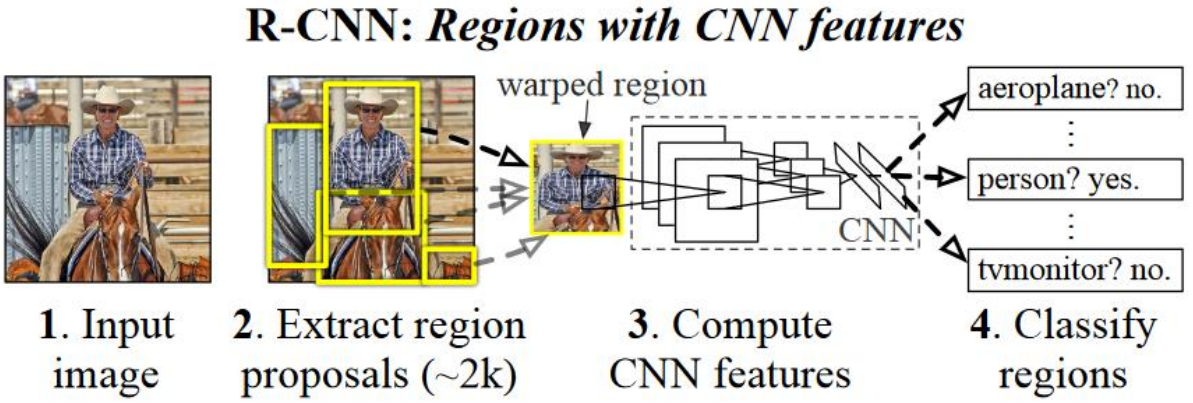

Figure 2. Regions with CNN features [4].

2.2. Fast Recurrent-Convolutional Neural Network (Fast R-CNN)

Ross et al. introduced Fast R-CNN, an improved framework of R-CNN, in 2015 [6]. Fast R-CNN algorithm is different from R-CNN algorithm in that it obtains the feature map by directly extracting features from the input image via a CNN and maps the candidate regions directly to the regions on the feature map. In addition, the Fast R-CNN algorithm employs. The Fast R-CNN algorithm is also used. Moreover, Fast R-CNN adopts Softmax to replace SVM to classify the target, so it is more accurate and efficient to detect target, as illustrated in Figure 3.

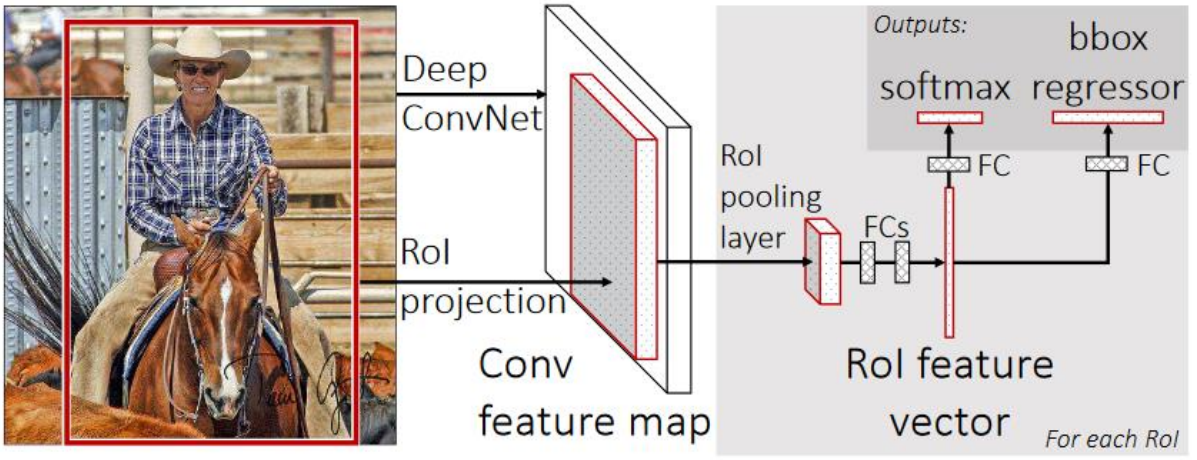

Figure 3. Fast R-CNN structure [5].

2.3. Faster Recurrent-Convolutional Neural Network (Faster R-CNN)

According to the information given above, a Faster R-CNN object detection algorithm was introduced in [7]. It aims to integrate the extraction of candidate frames into the network structure by designing

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the Region Proposal Networks network (RPN). It ultimately realizes the end-to-end network model, which greatly improves object detection performance.

2.4. You Only Look Once (YOLO)

Different from the previous classification based on target detection, this method takes target detection as a regression problem. It using the network to directly process the input image and output the type, position, and confidence level of the detected object. For example, the YOLO object detection algorithm divides the input image into grids of size S*S [8]. And when the center of the target object need to be detected falls within one of the grids, that grid will be responsible for detecting the target object. Each network predicts a fixed number of bounding boxes, which includes the coordinates of the bounding box and the confidence level of the corresponding classification, as shown in Figure 4.

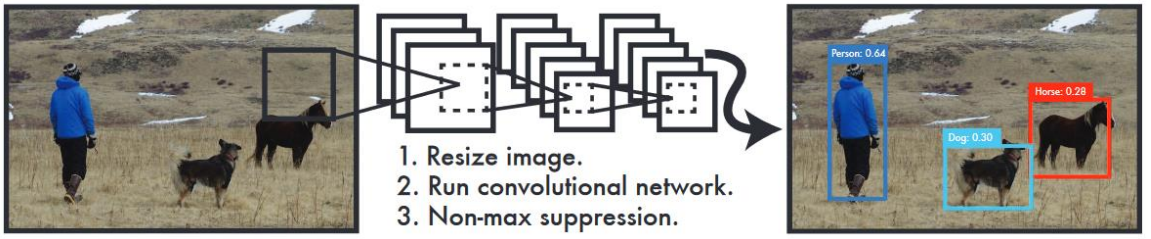

Figure 4. YOLO Detection System [7].

The YOLO algorithm is fast, but its drawback is that it is ineffective in detecting small targets.

2.5. YOLOv2

In addition, the YOLOv2 algorithm improves the YOLO network structure by adding a batch normalization layer and introducing a residual network structure, resulting in a 4% improvement in the mAP value [9].

2.6. YOLOv8

The YOLO family has been developed over several years, all of which are based on earlier releases in order to overcome constraints and improve performance [10]. The most recent YOLO algorithm is YOLOv8, which was launched in June 2023 by Ultralytics, which created YOLOv5 [11]. YOLOv8 is based on the same backbone as YOLOv5, but with a few modifications to the CSPLayer, which is now known as C2f, as illustrated in Figure 5.

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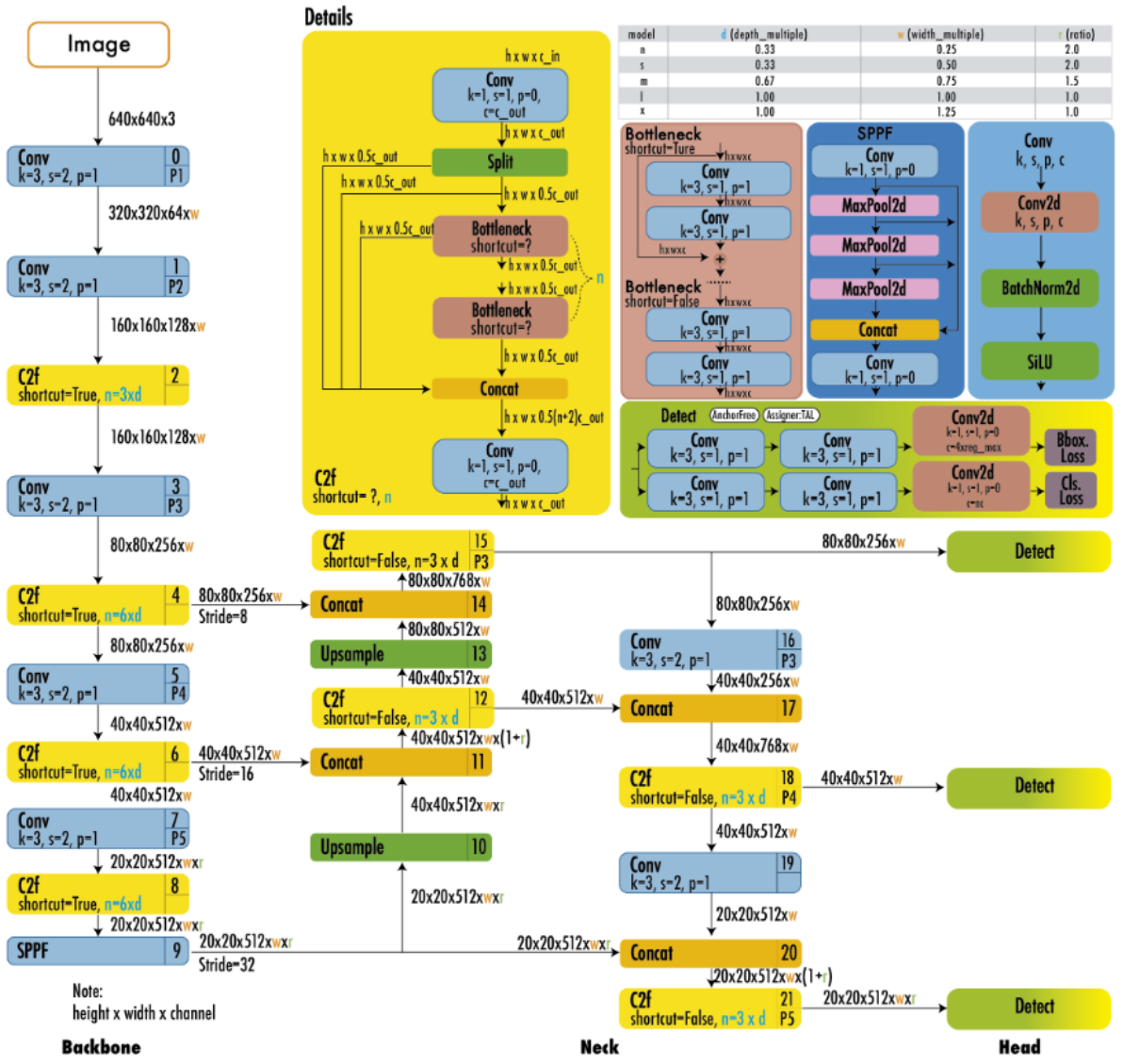

Figure 5. YOLOv8 Architecture [9].

The C2f module combines high level characteristics with contextual information to improve detection accuracy. YOLOv8 uses a non-stationary approach to address the issue of object, classification, and regression. In YOLOv8, the sigmoidal function was used to measure the likelihood of the presence of an object within the bounding box. YOLOv8 is now widely used in a wide range of applications, including image recognition, image recognition, and image recognition.

2.7. Summary

Overall, deep learning-based object detection algorithms have substantially exceeded classical object detection approaches and have gradually become the mainstream algorithms in the current object detection field.

3. Behavioral decision-making technology

Decision-making technology, as the core embodiment of intelligent and efficient completion of various driving tasks by self-driving vehicles, must effectively cope with the challenges brought by the uncertainty of information in complex environments to satisfy the needs of vehicle safety, economy

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and passenger comfort. Therefore, intelligent decision-making technology in complex traffic scenarios has become an important label for autonomous driving intelligence.

3.1. Reinforcement Learning (RL)

Progress in Reinforcement Learning has made a significant contribution to developing autonomous driving decision-making methods [12]. RL is based on Markov Decision Process (MDP) using closed-loop learning in the form of autonomous iterative learning using the payoff function as an incentive and exploratory trial-and-error methods, as shown in Figure 6, to gradually improve the decision-making ability [13]. RL-based autonomous driving decision-making technology has better autonomous decision-making ability, and can guide the corresponding driving behavior based on the effective reward function (safety, comfort, etc.).

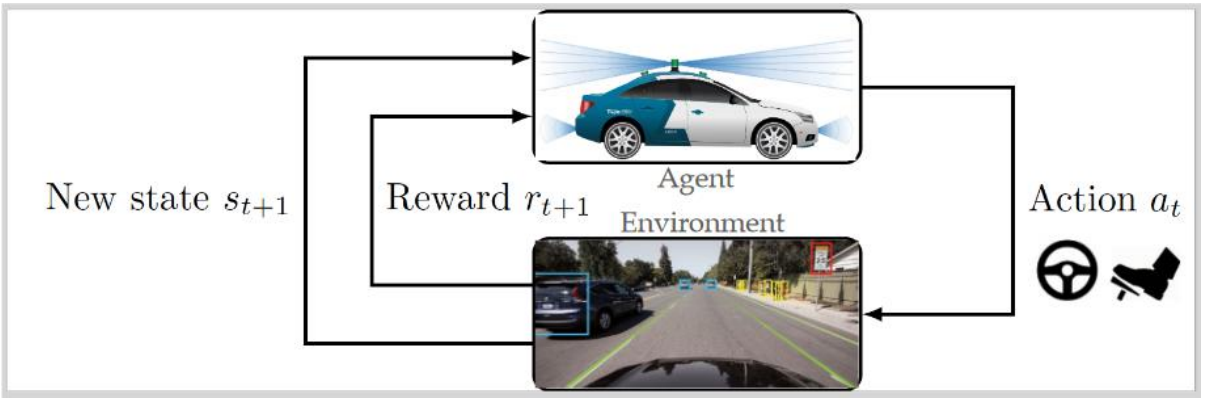

Figure 6. A diagram of reinforcement learning for a self-driving vehicle [11].

3.2. Deep Reinforcement Learning (DRL)

Deep Learning (DL) has become one of the most widely used techniques globally in recent years. Only when Deep Q-Network (DQN) was published did DRL truly break the bounds of autonomous decision-making [14]. Many researchers have applied Deep Neural Networks (DNN) to approach the behavior value function, integrate DL's perception capability with RL's decision-making capability, and make use of the picture taken from the camera, the simulation interface, etc., as State input, to better accomplish the tasks of vehicle lane keeping and obstacle avoidance, as shown in Figure 7(b) [15].

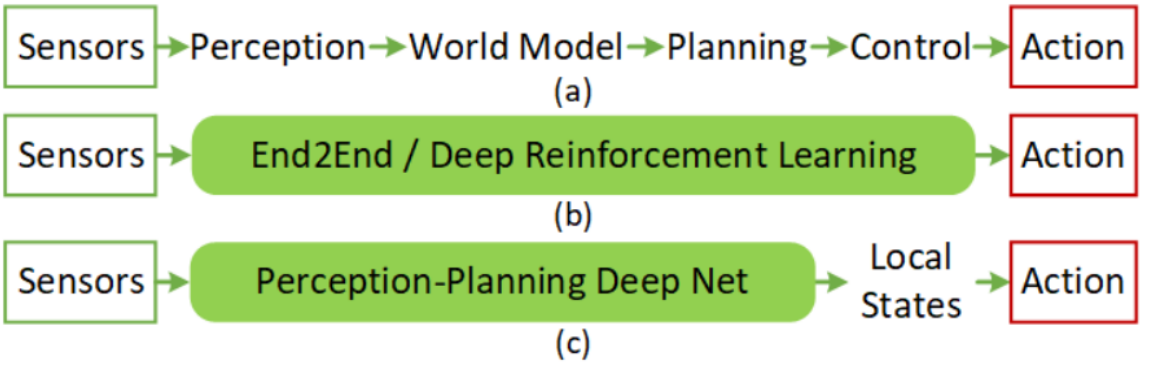

Figure 7. From a traditional modular pipeline method to a perception-planning DNN method for autonomous vehicles. (a) Vehicle navigation system based on traditional human-designed algorithms. (b) DRL-based approach. (c) NeuroTrajectory approach. [15].

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Based on DRL, Grigorescu et al. also proposed NeuroTrajectory [16]. It this is a multiobjective neuroevolution method for adaptive control, in which the goal is to predict the expected state path of an autonomous vehicle in a given region, as shown in Figure 7(c). Compared with deep reinforcement learnin's approach, which predicts the best behavior for a given time, Grigorescu et al calculated the optimum sequence of states available for movement control.

3.3. Other reinforcement learning algorithms

Aiming at the problems of sample complexity, sensitivity of hyperparameters, interpretability and security of RL algorithms, scholars have carried out cutting-edge researches on the following aspects for single-intelligence decision-making: Inverse Reinforcement Learning (IRL), Hierarchical Reinforcement Learning (HRL), Meta Reinforcement Learning (Meta RL), Offline Reinforcement Learning (Offline RL), Multi-task Reinforcement Learning (MTDRL), and so on, Hybrid Reinforcement Learning, etc., see Table 1. Meanwhile, Migration Reinforcement Learning, Quantum Reinforcement Learning, Distributed Reinforcement Learning, Transformer Reinforcement Learning, Secure Reinforcement Learning, Bayesian Reinforcement Learning, Interpretable Reinforcement Learning, and so on, have been hot research topics recently.

Table 1. RL's main frontier direction.

Algorithm	Main Idea	Common algorithms
IRL	Inversely extrapolating Reward, the Agent learns how to solve complex problems through expert demonstrations	Maximum Planning, Maximum Information Entropy, Relative Entropy, GAIL, HAIRL
HRL	The idea of divide and conquer through gradual achievement of goals or multi-level control is adopted to break down complex problems into sub-problems	Option-Critic, h-DQN, H-DRLN, h-DDPG, FuN, HER, HIRO, HAC, HSP, DIAYN, DADS
Meta RL	Gain historical experience from past missions to quickly adapt to new tasks and get the optimal strategy accordingly.	Meta-RL, RL2, SNAIL, MetaGenRL, LPG, MAML, Reptile, EPG, PEARL, MQL
Offline RL	Without interacting with the environment, the agent only learns empirical knowledge from the obtained data.	BEAR, BRAC, REM, CQL, IQL, Onestep, AWR, AWAC, BEAR, CQL
MTDRL	Based on shared representation, multiple related tasks are put together to learn	PathNet, Distral, PopArt, DISTRA, IMPALA

3.4. Inverse Reinforcement Learning (IRL)

For the RL frontier decision-making technology for single-vehicle intelligent driving, the widely used and relatively mature frontier mainstream are IRL, HRL and Hybrid Strategy Algorithms, and all of them have made breakthrough progress.

IRL originates in imitation learning, where experts' decisions are considered optimal or near-optimal strategies, i.e., the cumulative Reward generated by the expert's strategy is set to be the highest [17]. In other words, IRL aims to learn reward functions from human drivers. This method is based on the actual driving behaviour of the driver to study the reward function and produce a human-like's driving path. IRL is based on the perspective of maximum marginalization or probabilistic models, which infer the Reward from the existing strategies or observed expert behavior, thus improving the problems of excessive Reward error, sparse rewards, and convergence difficulties, as shown in Figure 8.

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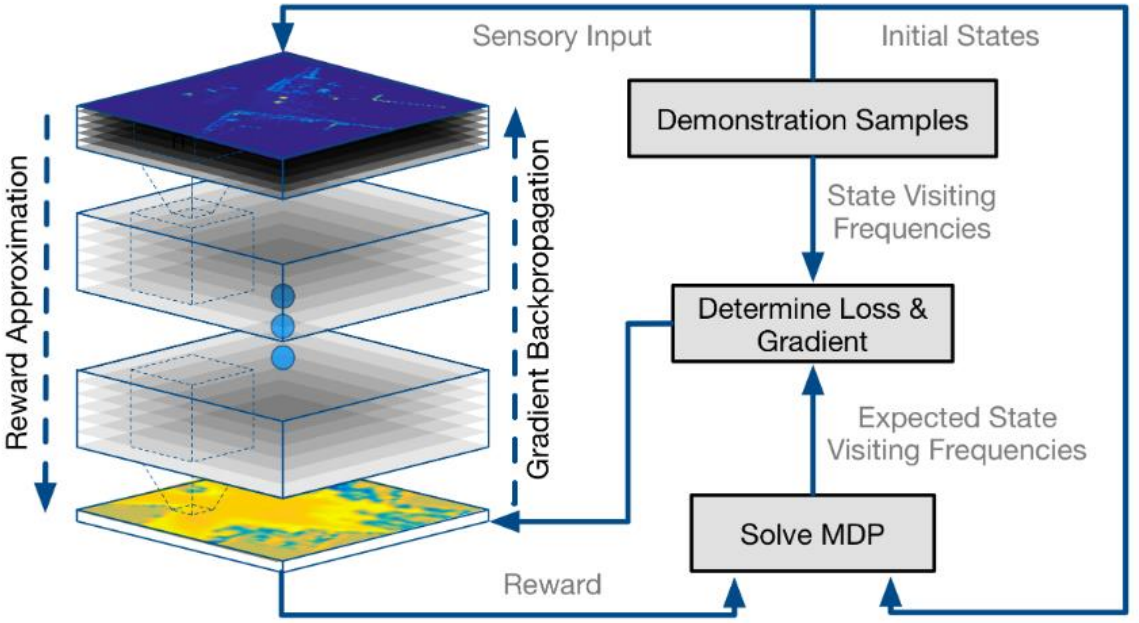

Figure 8. The training schema for neural networks in the Maximum Entropy paradigm for Inverse Reinforcement Learning (IRL) [16].

3.5. Hierarchical Reinforcement Learning (HRL)

Based on the idea of discrete and continuous hierarchical driving, the HRL algorithm uses MDP and Partially observable Markov decision process (POMDP) as the mathematical basis to establish the framework of discrete upper-level decision-making and continuous lower-level execution, as shown in Figure 9 [18]. Different local strategies in the hierarchical system are treated as an independent sub-function, for example, the total strategy of driving on the main highway can be subdivided into several independent sub-tasks, such as left/right lane change, lane keeping and following. It simplifies the State space capacity, which can better cope with problems such as dimensional catastrophe that may occur in RL classical algorithms and improve the overall decision performance.

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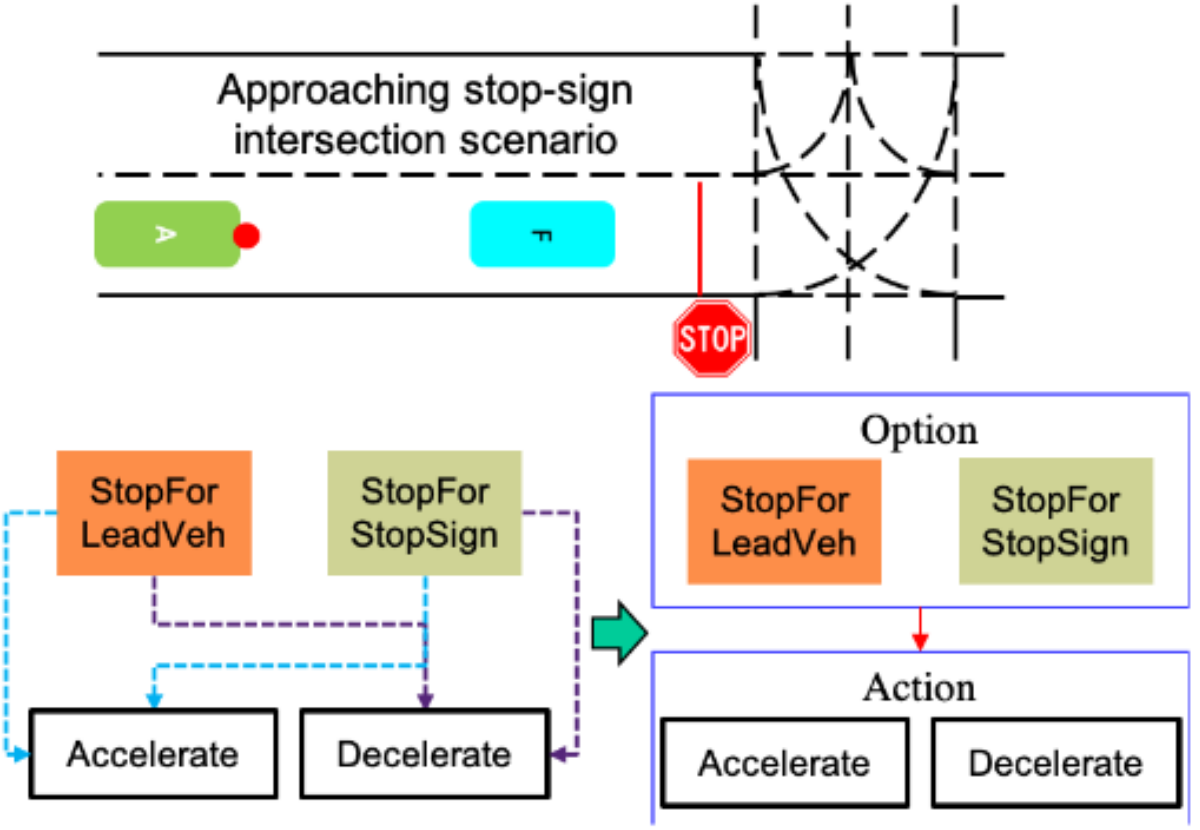

Figure 9. Heuristic-based structure vs. HRL-based structure [18].

3.6. Hybrid strategy algorithms

When directly adopting an end-to-end scheme in solving complex decision-making tasks for autonomous driving, there are difficulties in framework design due to the many influencing factors to be considered. A hybrid strategy algorithm that combines the composition of multiple decision-making schemes can be compatible with the characteristics of multiple cases and improve the decision-making capability [19].

4. Conclusion

In recent years, thanks to mankind's continuous pursuit and exploration of intelligent industry and other technologies, intelligent vehicles have gradually become the focus of research and a hot topic in today's society because of their important value and broad prospects. From the perspective of functional structure, intelligent vehicle navigation system is mainly composed of environment sensing, autonomous positioning, path planning, decision control and other modules. Among the above functional modules, environment sensing technology is the foundation of intelligent vehicle navigation system, and it is also one of the biggest obstacles to the mass production and commercialization of intelligent vehicles. Deep learning based object detection algorithms have a high level of feature expression capability and outstanding detection correctness, due to the fact that they do not require manual feature design. Most of the recent studies on object detection have been successfully applied to deep learning-based object detection algorithm, and they have been widely used in many applications. Another module that cannot be ignored is the decision control module. Intelligent decision-making ability is the core index for measuring and evaluating the ability of automatic driving. Reinforcement learning technology can be effectively used for different levels of automatic driving decision-making tasks in the simulation environment. After the development and application of RL-related technologies and cutting-edge algorithms, the training efficiency, convergence and stability, and scene

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generalization ability have been improved to a certain extent. Still, in addition to specific scenarios of automatic driving vehicles, the existing relevant research has not been carried out in the actual environment. The RL-based decision-making technology has many difficulties in engineering and landing. RL-based autonomous driving decision-making technology has many difficulties in engineering landing.

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