

An Overview of Perception and Decision-Making in Autonomous Systems in the Era of Learning

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Abstract

Autonomous systems possess the features of inferring their own ego-motion, autonomously understanding their surroundings, and planning trajectories. With the applications of deep learning and reinforcement learning, the perception and decision-making abilities of autonomous systems are being efficiently addressed, and many new learning-based algorithms have surfaced with respect to autonomous perception and decision-making. In this review, we focus on the applications of learning-based approaches in perception and decision-making in autonomous systems, which is different from previous reviews that discussed traditional methods. First, we delineate the existing classical simultaneous localization and mapping (SLAM) solutions and review the environmental perception and understanding methods based on deep learning, including deep learning-based monocular depth estimation, ego-motion prediction, image enhancement, object detection, semantic segmentation, and their combinations with traditional SLAM frameworks. Second, we briefly summarize the existing motion planning techniques, such as path planning and trajectory planning methods, and discuss the navigation methods based on reinforcement learning. Finally, we examine the several challenges and promising directions discussed and concluded in related research for future works in the era of computer science, automatic control, and robotics.

Index Terms - Autonomous system, perception, decision-

making, SLAM, deep learning, reinforcement learning

1. Introduction

In recent years, with the rapidly developments in learning systems, such as deep learning and reinforcement learning, they have been widely applied in various fields in smart grid [1], biology [2], finance [3], object detection [4], industrial production processes [5], and particularly in the autonomous systems of robots. Autonomous systems have gained a broad application prospect in various industries, such as autonomous robots [6] and vehicles [7]. Although current autonomous systems can only perform single, simple, and repetitive tasks, such as aided driving [8] and transportation [9], the future of autonomous systems has significant potential. Intelligent and autonomous systems are the ultimate aim, which can perform advanced tasks autonomously, interact with humans, and even work better than humans [10]. For example, there is no drunk or tired driving in autonomous vehicles. Primarily, autonomous vehicle systems should have the ability of autonomous or obstacle recognition, which heavily rely on the results of in-depth perception, intelligent decision-making, and accurate control [11]. The architecture of autonomous systems is illustrated in Fig. 1. Based on their perceiver [12], autonomous systems know where they are and what their surroundings look like by covering localization, mapping, and understanding the environment. A reasonable trajectory is planned by a decision-making module considering the mission requirement and utilizing the priori knowledge of the environment [13]. Finally, autonomous systems can reach the designated place autonomously and complete advanced missions by combining the results of perception and decision-making with control signals.

Perceiving and understanding the environment are the basic elements of autonomous systems [12]. The development and application of simultaneous localization and mapping (SLAM) have offered robots the ability to locate themselves and model the environment, which has significantly expanded the autonomy and intelligence of robots. With the

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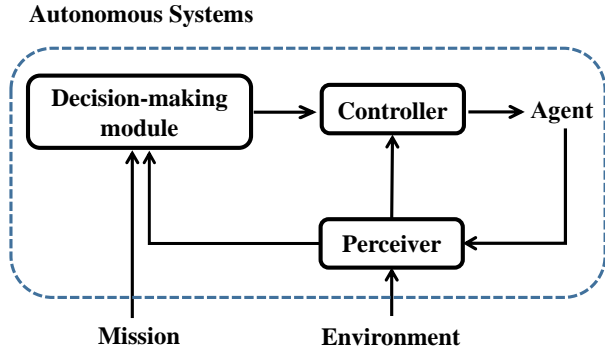


Figure 1. An illustration for the autonomous systems.

help of SLAM, autonomous systems use different sensors to simultaneously collect environmental information to model their surroundings and estimate their current state [14].

Perceiving the environment. A good perception and understanding of the surrounding environment are indispensable for autonomous systems such as self-driving cars. SLAM algorithms are widely applied to model the environments into different types based on the actual requirements, including sparse map [15], semi-dense map [16], dense map, [17] and semantic map [18], as shown in Fig. 2. Sparse maps imply that only a set of key-features are collected from the environment, such that the representation of the environment is rather abstract and only supports the simple localization requirement. Semi-dense map constructs more points, but important structural characteristics of the objects are still not apparent. Therefore, the dense mapping process is proposed to almost completely reconstruct the environment and utilize the information captured by visual sensors. Thus, dense maps can be used for various tasks, such as navigation [19] and visualization [17]. Although the geometric structure of surroundings in dense representation is clearly perceived and modeled, a high-level understanding of the 3D environment is still lacking. Hence, some related works [20, 21] incorporated semantic understanding into the map representations. Autonomous systems can identify different objects in the environment based on semantic maps, which enables them to perform more advanced interactive tasks.

Perceiving their own state. The state of an autonomous vehicle is described by its position and orientation. Understanding the current state is important for autonomous systems, which is the main precondition of autonomous control. SLAM supported by different sensors such as visual and inertial [22, 23], plays a crucial role in self-localization and ego-motion estimation. The accurate state estimation can be provided by SLAM by using only several simple sensors without the assistance of any external positioning device (e.g., Global positioning system, Ultra-wideband location, Vicon system).

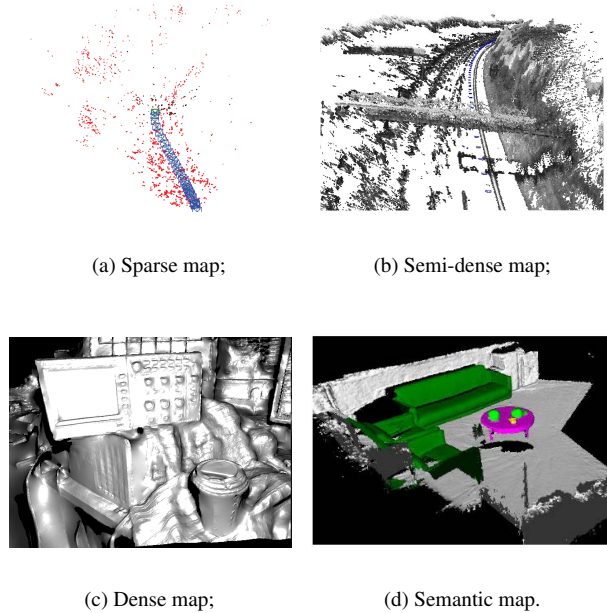


Figure 2. The environments are represented in different types. (a): Sparse map is produced by ORB-SLAM2 [15]. (b): Semi-dense map is produced by LSD-SLAM [16]. (c): Dense map is produced by DTAM [17]. (d): Semantic map is produced by DA-RNN [18].

Decision-making. The ability of autonomous decision-making is also essential in autonomous systems. When an autonomous vehicle is assigned a destination, it requires the capabilities of planning a reasonable path or trajectory. Therefore, this review focuses on the aspect of autonomous trajectory planning in autonomous systems. When a mission is given, autonomous systems must arrive at the designated place to complete the specific task [24]; reaching there is the first and basic decision-making problem. This issue often encounters various degrees of difficulties and challenges, such as real-time perception [25], under energy saving restrictions [13]. Poor or untimely decisions may lead to terrible results, such as collision and crash. Trajectory planning algorithms aim to provide reasonable paths for vehicles to reach the destination, and these paths should avoid possible collisions with static or dynamic obstacles and satisfy the dynamics of the vehicles.

Learning-based methods for perception and decision-making. With the developments in deep learning [26], deep neural networks, especially convolution neural networks (CNNs), have demonstrated outstanding performance in image processing [27, 28], natural language processing [29, 30], and motion estimation [31], among others. The impact of deep learning on perception is transformational, and it has made significant advances in autonomous vehicles [12]. For example, CNN-based models are widely used in relevant works of environment perception, such as monocular

depth estimation [32], ego-motion prediction [31], objective detection [4], and semantic segmentation [33]. Furthermore, to overcome the shortcomings (e.g., running in low texture or high dynamic scenes) and improve the robustness of the current SLAM methods, attempts have been made to incorporate SLAM with deep learning and satisfactory results have been obtained [34]. Reinforcement learning has also been widely studied in biology [2], finance [3], and control [35]. Related works demonstrate that reinforcement learning exhibits good performance in robotic navigation [36] because it implements the navigation problems in an end-to-end manner. Unlike some well-written reviews [12, 14, 37], this survey mainly focuses on surveying the learning-based SLAM related works, as well as the representative results for decision-making in autonomous systems.

The rest of the paper is organized as follows: Section II introduces related works on perception, including a brief review of traditional SLAM methods, deep learning-based perception, and methods combining deep learning with SLAM. Section III provides an overview of the trajectory planning solutions and reinforcement learning-based navigation. Section IV summarizes the deficiencies and challenges of existing perception and decision-making methods, and provides some ideas on future directions. Finally, this survey is concluded in Section V.

2. Autonomous Perception

In autonomous vehicle, determining a comprehensive understanding environment and its current state are the basic and important tasks, which can be efficiently solved by SLAM algorithms. Cadena *et al.* [12] reviewed the related works on SLAM over the last 30 years in detail. They revisited and answered several important and meaningful questions related to SLAM and stated that “SLAM is necessary for autonomous robots”. Furthermore, they discussed the accomplishments and challenges of SLAM. Readers who want to learn more about the classical SLAM methods can refer to [12, 37]. Different from previous review papers, in this section, we mainly focus on the application of deep learning algorithms in perception by subdividing them into three types.

2.1. Geometric methods-based perception

Traditional environment perception: SLAM is a common perception method in current autonomous systems. Compared with the SLAM systems that use Lidar sensors [79, 80], visual sensors such as RGB cameras can provide more information of scenes and have been widely investigated in recent years owing to their portability. Therefore, we briefly summarize different types of visual SLAM methods in a chronological order first, as presented in Table 1. Their categories of optimization, maps, and sensors are enu-

merated in detail. From Table 1, we find that filtering-based SLAM methods are widely studied in the initial stage owing to their low computational burden. With the developments in computer science, optimization-based SLAM methods have become popular in recent years due to their higher accuracy. Meanwhile, dense maps are usually constructed by direct methods based on RGB-D sensors, like [49–51], *etc.* In addition, new sensors, such as event cameras, and multi-sensor data fusion are attracting significant attention and research prospects [56, 59, 72, 75]. In this section, we communicate the basic principles of the three classical monocular SLAM solutions, including feature-based methods [22], direct methods [16], and semi-direct methods [55]. The main difference between these three methods is the pose optimization by minimizing either the reprojection error, photometric error, or both [81].

Feature-based methods have dominated SLAM for a long time because of their robustness and effectiveness. The feature-based methods can be divided into three parts, including image input, feature extraction and matching, tracking and mapping. When a camera captures the images, artificially designed features (like SIFT [82], SURF [83] and ORB [84]) are extracted for each image and described with special descriptors (like BRIEF [85]). In order to accurately identify and match the same features between frames, these hand-made features and their descriptors are designed with special properties, like reproducibly, efficiency, luminosity invariance, and rotation invariance [85]. After feature matching, the correspondences of pixels between frames and the map are used to localize the camera and extend the map. Finally, the poses and local map are optimized by minimizing the reprojection error. Generally, an independent thread is designed in a feature-based SLAM to detect the loop closure [15]. Loop detection is the key of building a globally consistent map and eliminating the scale-drift. The performance of feature-based methods relies on the correct matching, which means that they are not robust in low texture and repeated texture scenes [16]. However, as long as the features can be accurately matched, even if the inter-frame movement is large, feature-based methods can also have high robustness [14]. *Direct methods* cancel the process of feature extraction and matching, and the photometric information of pixels is used directly during tracking and mapping [16, 86], which are different from feature-based methods. Direct methods regard the pose estimation as a nonlinear optimization problem and iteratively optimize the initial motion guess by minimizing the photometric error [16]. Since there is no need for the process of feature extraction and descriptor calculation, direct methods are faster than feature-based methods. Furthermore, direct methods have no special requirement for environment texture but photometric gradient. Hence, they are robust in low texture and repeated texture scenes. *Semi-direct methods* firstly

Table 1. A summary of major visual SLAM methods. “Mono.” denotes the monocular camera, and “stereo” stands for stereo camera.

Year	Reference	Method		Type			Map			Sensor
		Filtering-based	Optimization-based	Direct	Semi-direct	Feature-based	dense	semi-dense	sparse	
2003	Real-time SLAM [38]	✓							✓	Mono.
2004	Davison <i>et al.</i> [39]	✓							✓	Mono.
2004	Meltzer <i>et al.</i> [40]	✓							✓	Mono.
2005	CV-SLAM [41]	✓							✓	Mono.
2006	Smith <i>et al.</i> [42]	✓							✓	Mono.
2007	MonoSLAM [43]	✓							✓	Mono.
2007	PTAM [44]		✓						✓	Mono.
2007	Mourikis <i>et al.</i> [45]	✓							✓	Mono.
2008	Silveira <i>et al.</i> [46]		✓	✓					✓	Mono.
2009	Migliore <i>et al.</i> [47]	✓				✓			✓	Mono.
2010	Newcombe <i>et al.</i> [48]		✓		✓		✓			Mono.
2011	DTAM [17]		✓	✓			✓			Mono.
2011	KinectFusion [49]	✓		✓			✓			RGB-D
2012	Kintinuous [50]		✓	✓			✓			RGB-D
2013	Whelan <i>et al.</i> [51]		✓	✓			✓			RGB-D
2013	Weikersdorfer <i>et al.</i> [52]	✓		✓				✓		Mono., Event camera
2013	Kerl <i>et al.</i> [53]		✓	✓			✓			RGB-D
2013	Endres <i>et al.</i> [54]		✓	✓			✓			RGB-D
2013	Li <i>et al.</i> [23]	✓							✓	Mono.,IMU
2014	SVO [55]		✓					✓		Mono.
2014	LSD-SLAM [16]		✓	✓				✓		Mono.
2014	Weikersdorfer <i>et al.</i> [56]		✓	✓					✓	RGB-D, Event camera
2015	Stereo-LSD-SLAM [57]		✓	✓				✓		Stereo
2015	ORB-SLAM [22]		✓	✓					✓	Mono.
2015	Leutenegger <i>et al.</i> [58]		✓	✓					✓	Stereo
2015	Bloesch <i>et al.</i> [59]	✓		✓					✓	Mono.,IMU
2016	ElasticFusion [60]		✓	✓			✓			RGB-D
2016	Forster <i>et al.</i> [61]		✓			✓			✓	Mono., IMU
2016	SVO 2.0 [62]		✓		✓				✓	Mono., Multicamera
2016	EVO [63]		✓	✓				✓		Event camera
2017	DSO series [64–66]		✓	✓					✓	Mono., Stereo,IMU
2017	ORB-SLAM2 [15]		✓	✓					✓	Mono., Stereo, RGB-D
2017	Bundlefusion [67]		✓	✓			✓			RGB-D
2017	Mur <i>et al.</i> [68]		✓	✓					✓	Mono., IMU
2018	ProSLAM [69]		✓	✓					✓	Stereo
2018	Sun <i>et al.</i> [70]	✓							✓	Stereo, IMU
2018	ICE-BA [71]		✓	✓					✓	Mono., IMU
2018	Zhou <i>et al.</i> [72]		✓	✓				✓		Stereo, event camera
2018	VINS-mono [73]		✓	✓					✓	Mono., IMU
2018	Lee <i>et al.</i> [74]		✓		✓				✓	Mono.
2019	Geneva <i>et al.</i> [75]	✓				✓			✓	Mono., IMU
2019	BAD SLAM [76]		✓	✓			✓			RGB-D
2019	RESLAM [77]		✓		✓		✓			RGB-D
2019	FMD Stereo SLAM [78]		✓		✓				✓	Stereo

establish feature correspondences based on direct methods, which is the main difference from other methods [55, 62]. The principle of epipolar line constraint is applied to match the same features on the epipolar line. After matching the features, a minimizing the reprojection error step is used to optimize the solved pose. Therefore, semi-direct methods solve the tracking problem by minimizing the photometric error and the reprojection error. Semi-direct methods also have a high requirement on image quality and sensitive to photometric changes. In conclusion, although the architecture of SLAM algorithm has developed very maturely over the past 30 years and the three kinds of approaches have achieved good performance in some scenes, their robustness and accuracy in complex scenes (like high-dynamic, large scale environment) still need to be further improved [12].

High-level environment perception: Autonomous systems require a high-level understanding of their surroundings to complete advanced tasks. For instance, autonomous vehicles should have an understanding of the areas that are drivable and those that have obstacles. However, the environments modeled by traditional SLAM methods are represented by point clouds, which only contain the location of the point and cannot provide any high-level information

about 3D objects. Although the current metric representation for SLAM executes some basic tasks, such as localization and path planning, it is still insufficient for some advanced tasks, such as human-robot interaction, 3D object detection, and tracking. Therefore, high-level and expressive representations will play a key role in the perception of autonomous systems. To obtain high-level perception, an object-level environment representation [87] was proposed in 2011 by modeling the objects in advance and matching them in a global point cloud map. Salas *et al.* [88] extended this work in [87]. They created an object database to store the 3D models generated by KinectFusion [49] and computed the global descriptor of every object model for quick matching based on [89]. They also demonstrated that object-level mapping is useful for accurate relocalization and loop detection. Contrary to building the models in advance, Sunderhauf *et al.* [90] proposed an online modeling method for generating the point cloud models of objects, along with a novel framework for SLAM by combining object detection and data association to obtain semantic maps. In comparison to an object-level maps, pixel-level semantic maps are more precise because they present the semantic information of each point in the maps. To improve the ac-

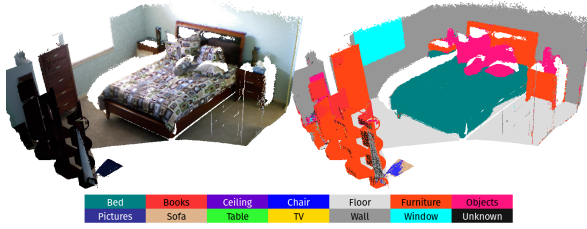


Figure 3. An example of sense semantic map produced by [94]. Left: a dense surfel-based reconstruction of a bedroom. Right: the map semantically annotated with the semantic labels. With the help of semantic information, robots will get a high-level awareness of their surroundings.

curacy of segmentation and semantic mapping, conditional random fields (CRFs) have been widely used in related works. A voxel-CRF model was presented in [91] to associate the semantic information with 3D geometric structure, and a dense voxel-based map with semantic labels was constructed. For consistent 3D semantic reconstruction, Hermans *et al.* [92] proposed a novel 2D-3D label transfer method based on CRFs and Bayesian updates. Considering the intrinsic relationship between geometry and semantics, Kundu *et al.* [93] utilized the constraints and jointly optimized semantic segmentation with 3D reconstruction based on CRFs. Gan *et al.* [21] focused on the continuity of maps and valid queries at different resolutions, and exploited the sparse Bayesian inference for accurate multi-class classification and dense probabilistic semantic mapping. With the help of semantic maps, autonomous systems can obtain a high-level understanding of their surroundings, and they can easily know “which and where is the desk”.

2.2. Deep learning-based perception

With the developments in deep learning, utilizing deep neural networks to solve computer vision has become a hot topic in recent years. Many sub-topics of SLAM for environment perception have been widely studied based on deep learning, such as monocular depth estimation and ego-motion prediction, which will be specified in the following sections.

2.2.1 Depth perception

Depth estimation is helpful in understanding the geometric structure of environments. Geometry-based approaches recover the depth information by using structure-from-motion (SfM) methods with multi-view information [132, 133], which is complex in computation, and it is difficult to construct dense depth maps using them. Related works on stereo depth estimation have been summarized by Scharstein *et al.* [134]. Estimating the depth from a single image is less straightforward without the help of deep learn-

ing, which requires significant prior knowledge [135, 136]. Deep neural networks enable the recovery of depth information from single images in an end-to-end manner. To the best of our knowledge, Eigen *et al.* [95] first designed a deep neural network framework to regress the monocular depth. They introduced a coarse-scale network to predict the depth coarsely and another fine-scale network to refine the detail. Although the predicted depth map is still far from the truth value, it proves the feasibility of neural networks for monocular depth estimation. Instead of refining the depth map by additional networks, Li *et al.* [96] designed a hierarchical CRF to improve the predicted depth and achieve competitive results. Similarly, by considering the continuous and smooth characteristics of monocular depth value, Liu *et al.* [97] proposed a novel deep convolution neural field module for monocular depth estimation, which incorporates continuous CRFs into deep CNNs and improved the performance. Further, with the developments in optical flow estimation based on CNNs, Mayer *et al.* [98] extended the framework of optical estimation to disparity estimation and trained the disparity network with a scene flow network. To incorporate contextual information, 3D convolution and deconvolution were used in the disparity learning framework [99]. Moreover, instead of recovering the depth maps from single images, they regressed the depth information from stereo image pairs. To solve the slow convergence and local solutions caused by minimizing the mean squared error, Fu *et al.* [100] proposed an ordinal regression loss function and a novel training strategy called SID (spacing increasing discretization). In addition, above proposed methods were trained only on the datasets collected by the same camera, which limits the transferability of the depth estimation network on different cameras. Considering the generalization ability of the network on different cameras, Facil *et al.* [101] considered the role of the camera model in depth estimation and added the camera model into the network framework, thereby improving the robust generalization of the depth model. In order to better evaluate the performance of various methods, a widely used evaluation method based on the error calculation methods proposed in [95, 96] was developed, and evaluation indicators (*Abs Rel*, *Sq Rel*, *RMSE*, *RMSE log*, δ) were formed as:

- **RMSE** = $\sqrt{\frac{1}{T} \sum_{i \in T} \|d_i - d_i^{gt}\|^2}$,
- **RMSE log** = $\sqrt{\frac{1}{T} \sum_{i \in T} \|\log(d_i) - \log(d_i^{gt})\|^2}$,
- **Abs Rel** = $\frac{1}{T} \sum_{i \in T} \frac{|d_i - d_i^{gt}|}{d_i^{gt}}$,
- **Sq Rel** = $\frac{1}{T} \sum_{i \in T} \frac{\|d_i - d_i^{gt}\|^2}{d_i^{gt}}$,
- **Accuracies**: % of d_i s.t. $\max(\frac{d_i}{d_i^{gt}}, \frac{d_i^{gt}}{d_i}) = \delta < thr$,

Table 2. A summary of deep learning-based depth and ego-motion estimation.

Methods	Years	Training Data	Supervisory signal			Mission		
			Supervised	Semi-supervised	Unsupervised	Depth	Pose	Other tasks
Eigen <i>et al.</i> [95]	2014	RGB + Depth	✓			✓		-
Li <i>et al.</i> [96]	2015	RGB + Depth	✓			✓		Surface Normal
Liu <i>et al.</i> [97]	2015	RGB + Depth	✓			✓		-
Mayer <i>et al.</i> [98]	2016	RGB + Depth	✓			✓		-
Kendall <i>et al.</i> [99]	2017	Stereo images + Disparity	✓			✓		Disparity
Fu <i>et al.</i> [100]	2018	RGB + Depth	✓			✓		-
Facil <i>et al.</i> [101]	2019	RGB + Depth	✓			✓		-
Garg <i>et al.</i> [102]	2016	Stereo images		✓		✓		-
Godard <i>et al.</i> [103]	2017	Stereo images		✓		✓		-
Kuznetsov <i>et al.</i> [104]	2017	Stereo images + LiDAR		✓		✓		-
Poggi <i>et al.</i> [105]	2018	Stereo images		✓		✓		-
Ramirez <i>et al.</i> [106]	2018	Stereo images + Semantic Label		✓		✓		-
Aleotti <i>et al.</i> [107]	2018	Stereo images		✓		✓		-
Pilzer <i>et al.</i> [108]	2018	Stereo images		✓		✓		-
Pilzer <i>et al.</i> [109]	2019	Stereo images		✓		✓		-
Tosi <i>et al.</i> [110]	2019	Stereo images		✓		✓		-
Chen <i>et al.</i> [111]	2019	Stereo images		✓		✓		Semantic segmentation
Fei <i>et al.</i> [112]	2019	Stereo images + IMU + Semantic Label		✓		✓		-
Wang <i>et al.</i> [113]	2018	Mono. sequences		✓		✓	✓	-
Zhan <i>et al.</i> [114]	2018	Stereo sequences		✓		✓	✓	-
Li <i>et al.</i> [115]	2018	Stereo sequences		✓		✓	✓	-
Wang <i>et al.</i> [116]	2019	Stereo sequences		✓		✓	✓	Optical Flow
Zhou <i>et al.</i> [32]	2017	Mono. sequences			✓	✓	✓	Motion mask
Vijayanarasimhan <i>et al.</i> [117]	2017	Mono. sequences			✓	✓	✓	Motion flow and segmentation
Yang <i>et al.</i> [118]	2017	Mono. sequences			✓	✓	✓	Normal
Mahjourian <i>et al.</i> [119]	2018	Mono. sequences			✓	✓	✓	Principled Masks
Zou <i>et al.</i> [120]	2018	Mono. sequences			✓	✓	✓	Optical Flow
Yin <i>et al.</i> [121]	2018	Mono. sequences			✓	✓	✓	Optical Flow
Ranjan <i>et al.</i> [122]	2019	Mono. sequences			✓	✓	✓	Optical Flow, Motion segmentation
Wang <i>et al.</i> [123]	2019	Mono. sequences			✓	✓	✓	-
Li <i>et al.</i> [124]	2019	Mono. sequences			✓	✓	✓	-
Konda <i>et al.</i> [125]	2015	Mono. sequences + Pose	✓			✓		-
Kendall <i>et al.</i> [31]	2015	Mono. sequences + Pose	✓			✓		-
Costante <i>et al.</i> [126]	2015	Mono. sequences + Pose	✓			✓		-
Wang <i>et al.</i> [127]	2017	Mono. sequences + Pose	✓			✓		-
Xue <i>et al.</i> [128]	2018	Mono. sequences + Pose	✓			✓		-
Xue <i>et al.</i> [129]	2019	Mono. sequences + Pose	✓			✓		-
Clark <i>et al.</i> [130]	2017	Mono. sequences + Pose + IMU	✓			✓		-
Chen <i>et al.</i> [131]	2019	Mono. sequences + Pose + IMU	✓			✓		-

where d_i stands for the predicted depth and d_i^{gt} refers to the groundtruth of depth. thr denotes the threshold, usually 1.25, 1.25^2 , and 1.25^3 .

Although these deep learning-based depth estimation methods achieved good depth prediction, their training processes significantly depend on the ground truth, which is expensive and difficult to acquire. Therefore, instead of using the error between depth estimation and ground-truth as the supervisory signals, attempts have been made to propose unsupervised or semi-supervised methods based on the new constraints by considering the spatial geometric inferences.

Garg *et al.* [102] presented an unsupervised monocular depth estimation framework based on view reconstruction. Stereo image pairs were used for the training process instead of large amounts of labeled training data, and the network could estimate the depth map from a monocular image with scale information during testing. During training, the depth map d_l was predicted and applied to calculate the disparity map D_{lr} between left and right images I_l , I_r through fB/d_l , where f and B represent the focal length and the distance between two cameras. Then the left image \hat{I}_l can be warped from the right image I_r by the motion of pixel x along the base-line $d_l(x)$, as shown in Fig. 4 (a), and the main constraint of stereo methods [102] can be formatted as:

$$\mathcal{L}_{lr} = \sum \| \hat{I}_l(x) - I_l(x) \|^2 = \sum \| I_r(x + D_{lr}) - I_l(x) \|^2 \quad (1)$$

Inspired by Mayer *et al.* [98] and Garg *et al.* [102], Godard *et al.* [103] proposed a fully CNN and a novel left-right disparity consistency loss function to improve the performance of the predicted monocular depth map. They also improved the view reconstruction loss by using L_1 and SSIM [137], which have been generally used in unsupervised learning methods recently and helps in improving the performance of networks:

$$\mathcal{L}_r = \alpha \frac{1 - SSIM(I_l, \hat{I}_l)}{2} + (1 - \alpha) \| I_l - \hat{I}_l \|, \quad (2)$$

where α is a balance weight usually set to 0.85. To enhance the supervisory signals, Kuznetsov *et al.* [104] proposed a semi-supervised method that considered the stereo view reconstruction error with the sparse ground-truth collected by the LiDAR sensor as the additional supervision, thereby achieving higher performance. Because the stereo-based methods suffer from occlusions and left image border, Poggi *et al.* [105] extended the previous works by simulating a trinocular setup, which ensured that the estimated monocular depth map was unaffected by these issues. Furthermore, they also proposed a semi-supervised framework that jointly trained the depth network with a semantic segmentation network [106], and the semantic segmentation network was trained with ground truth data. The experiments proved that these attempts are helpful for improving the accuracy of depth estimation. New network frame-

works and constraints are also considered to improve the accuracy of depth estimation, such as adversarial framework [107] and distillation framework [138]. Adversarial learning was used and compelling results were achieved [107, 108]. Pilzer *et al.* [109] considered the inconsistencies between raw images and cycle-reconstruction images, and designed an additional refinement network with the knowledge distillation framework to promote the performance of depth estimation. Similarly, Tosi *et al.* [110] proposed a novel framework by leveraging the refinement module and traditional algorithm, thereby achieving higher accuracy on depth prediction. Common sense knowledge, such as the relationship between depth and semantic information [111] or physical information, [112] have also been considered to improve the accuracy of the predicted depth maps.

2.2.2 Ego-motion perception

Geometry-based visual odometry methods solve the localization and tracking by minimizing the photometric error [64] or reprojection error [22]. Konda *et al.* [125] first estimated the motion information through deep learning-based methods by formulating pose prediction as a classification problem. Alex *et al.* [31] first demonstrated the ability of CNNs on 6-DOF pose regression. A deep CNN framework called PoseNet was designed for regressing monocular camera pose that could operate in different scenes in real-time. In [126], Costante *et al.* also used a deep CNN to learn high-level feature representation; the major difference from [31] is that the dense optical flow was calculated and used to estimate the ego-motion instead of feeding RGB images into the CNN directly. Considering the dynamics and relations between adjacent pose transformations, Wang *et al.* [127] and Xue *et al.* [128] used recurrent convolutional neural networks (RNN) for camera localization. Then, Xue *et al.* [129] further extended their work by incorporating two helpful modules named “Memory” and “Refining” into visual odometry (VO) tasks, which outperformed the state-of-the-art deep learning-based VO methods [128]. The traditional methods have proved that combining visual information with inertial information is helpful for improving the visual localization accuracy [58, 139, 140]; however, these visual-inertial odometry (VIO) methods suffer from difficulties in calibration, information fusion and time-stamp synchronization. Researchers believe that inertial information is also helpful in learning-based methods. Therefore, Clark *et al.* [130] proposed the first end-to-end VIO framework based on deep learning without the need for time-stamp alignment and manual calibration between different sensors. They used the CNN architecture to extract visual features and long short-term memory (LSTM) to extract the inertial features, and fused their features using a core LSTM processing module for pose regression. For better integra-

tion of visual and inertial features extracted by the deep neural networks, Chen *et al.* [131] presented a selective sensor fusion framework based on the attention mechanism, which achieved the desired results.

2.2.3 Joint perception of depth and ego-motion

Another unsupervised framework for depth and pose estimation was based on temporal geometric constraints, i.e., jointly training the depth network with a pose network using monocular videos. Training with stereo image pairs is similar to the case of monocular videos, and the main difference is whether the transformation between two frames (left-right images or front-back images) is known. Therefore, the stereo framework is also considered a semi-supervised method, which uses the known pose (between left-right images) as a supervisory signal [32, 121].

Zhou *et al.* [32] introduced an additional ego-motion prediction network to provide pose estimation between frames and jointly trained it with the depth network in an unsupervised manner. The key supervisory signal for this framework comes from the view synthesis error, which was computed by the view reconstruction algorithm:

$$p_{t-1} \sim K \hat{T}_{t \rightarrow t-1} \hat{D}_t(p_t) K^{-1} p_t, \quad (3)$$

where K denotes the camera intrinsics matrix. \hat{D}_t and $\hat{T}_{t \rightarrow t-1}$ are the predicted depth map and 6-DOF transformation between images I_t and source image I_{t-1} , respectively. Then, similar to [141], the differentiable bilinear sampling mechanism was used to process the warping images. To eliminate the influence of dynamic objects and occlusion on view reconstruction and training, Zhou *et al.* designed an explainability network to estimate these regions and improve the results. Their concurrent work [117] integrated the depth, motion, and segmentation into the same framework, which can be trained in a coupled manner. Following Zhou *et al.*'s work, Yang *et al.* [118] combined the surface normal representation with the depth estimation framework for more robust geometry constraints. A novel 3D geometric loss based on ICP [142] was designed in [119] and a mask network was used to eliminate the unreconstructed regions. Wang *et al.* [123] designed multiple masks to filter the mismatched pixel and make the learning process more efficient. Instead of using the poses predicted by the pose network, Wang *et al.* [113] used traditional direct RGB-D VO [143] to compute the pose and train the depth network. Recent approaches [120–122] leveraged multi-task learning into one framework and performed joint training using geometric constraints between tasks. The influence of dynamic objects and occlusion on view reconstruction was also considered in [122] by using a motion segmentation network. They also designed a competitive training method to coordinate the training process between multiple tasks. Zhan *et*

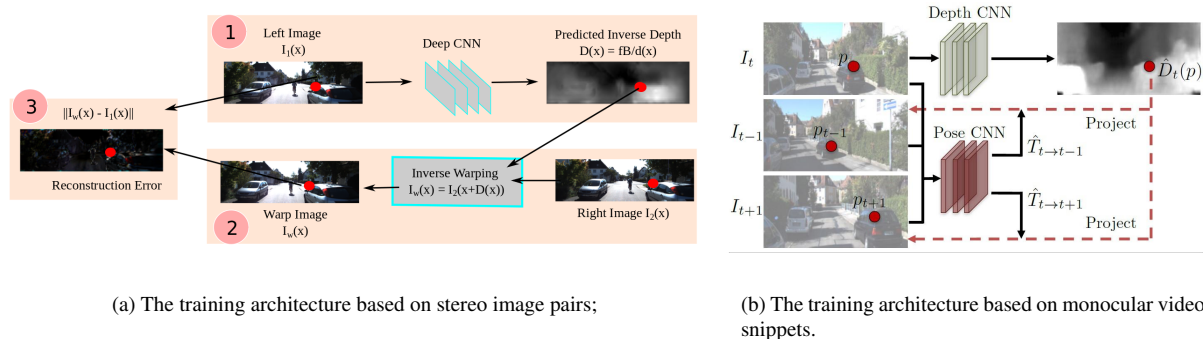


Figure 4. The training framework of a monocular depth estimation network. (a): the general architecture proposed in [102]. (b): the architecture proposed in [32].

al. [114], Li *et al.* [115], and Wang *et al.* [116] considered the constraints of both temporal and spatial geometry by training their depth network with stereo image sequences to solve the scale ambiguity problem of monocular methods. Different types of generative adversarial networks (GANs), like conditional GAN [144], stacked GAN [145] and Cycle GAN [146], are also widely applied to improve the accuracy of depth and pose estimation [108, 124, 147–151], and demonstrate the effectiveness of adversarial learning on depth prediction. In [108, 124, 148, 151], the synthesized images based on view reconstruction were sent to the discriminator along with raw images, and the difference between the synthesized and raw images was reduced by adversarial learning to optimize the training process of pose and depth networks. Meanwhile, the forward and backward sequences of videos were used in [152, 153] during training to utilize the geometric information. Different from the above works that only considered the accuracy of depth estimation, Poggi *et al.* [154] and Wofk *et al.* [155] considered the real-time performance of depth networks and designed a novel lightweight framework that could infer the depth map quickly on a CPU. We summarize the deep learning-based monocular depth estimation and pose prediction in Table 2. From the table, we find the development trend of pose and depth estimation, i.e., unsupervised, multi-sensors, and multi-tasks.

2.3. SLAM with deep learning

The methods combining SLAM with deep learning have also been widely studied and proved to effectively improve the performance of traditional SLAM methods.

2.3.1 Depth map estimation and SLAM

The combination of deep learning-based depth estimation and traditional SLAM methods has been proved to be effective in overcoming the monocular scale ambiguity,

thereby improving mapping and replacing the RGB-D sensors. Depth prediction was first introduced in dense monocular SLAM by Laina *et al.* [156]. Because the mapping process reduces the dependence on feature extraction and matching, this method has the potential to reconstruct low-texture scenes. Moreover, this work showed that the depth estimation network can replace the depth sensors (such as RGB-D) and can be used for dense reconstruction. Next, a real-time dense SLAM framework was proposed in [157]. They used the LSD-SLAM [16] as the baseline and fused the depth estimation and semantic information. Unlike the work by Laina *et al.* [156], where the depth estimation was directly used in SLAM, Tateno *et al.* [157] considered the predicted depth map as the initial guess of LSD-SLAM, and further refined the predicted depth value by the local or global optimization algorithms in SLAM. This method not only improved the robustness and accuracy of LSD-SLAM, but also overcame the issue of scale inconsistency in dense monocular reconstruction. Similarly, Yang *et al.* [158] proposed a novel semi-supervised disparity estimation network and incorporated it into direct sparse odometry (DSO) [95], thereby achieving a comparable performance to previous stereo methods. Recently, Loo *et al.* [159] presented a CNN-SVO pipeline that leveraged the SVO [55] with depth prediction network to improve the mapping thread of SVO.

2.3.2 Pose estimation and SLAM

Although pose networks have better real-time performance, combining pose estimation with traditional SLAM methods has been a largely under-explored domain. Our previous work [160] designed a self-supervised pose prediction network and incorporated it into DSO [95]. We considered the output of the pose network as the initial pose guess of direct methods, which replaced the constant motion model used in DSO; then, the initial pose was improved by the nonlinear optimization of DSO. This method effectively improved the tracking accuracy and initialization robustness of

the direct method when testing on the KITTI odometry sequences [161].

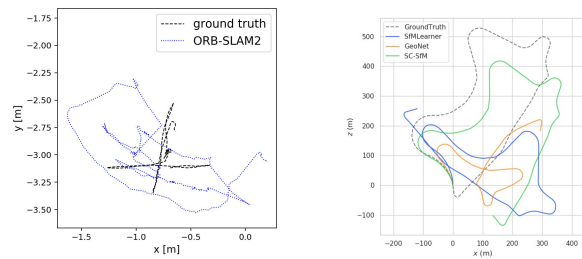
2.3.3 Image domain transfer and SLAM

Current SLAM methods have good robustness under specific domains, such as outdoor scenes with normal illumination conditions [161]. While driving in complex environments, such as during the night, in rain, and other scenarios, the perception of autonomous vehicles based on SLAM still faces various problems. Image domain transfer means that transferring the scene domains unsuitable for SLAM to the suitable domains; thus, the robustness of the SLAM algorithm is improved. Tracking in poor illumination conditions is still a big challenge for current SLAM systems [162]. Challenging light environments, such as night driving situations, affect the feature extraction and tracking process, which heavily reduce the robustness and stability of SLAM systems. To improve the performance of SLAM in challenging environments, classical vision methods have been extensively studied, such as designing a new metric [162] and proposing novel feature descriptor [163]. With the developments in image style translation [146, 164] and video synthesis [165, 166], deep learning-based image enhancement provides a new way for SLAM systems to overcome challenging environments [167, 168]. Gomez *et al.* [169] used deep neural networks to enhance the brightness constancy of image sequences captured from high dynamic range (HDR) environments. The experiments showed that learning-based image enhancement can improve the robustness and accuracy of SLAM in HDR environments. Because the illumination influences feature extraction and matching, Jung *et al.* [34] proposed a new framework called multi-frame GAN that translated the image domain from bad illumination to normal illumination suitable for current SLAM methods, which effectively improved the robustness of SLAM in low light environments.

2.3.4 Object detection, semantic segmentation, and SLAM

we consider the following three problems:

Scene understanding: With the developments in deep neural networks, several detection and segmentation methods are proposed based on deep learning. Methods for object detection and image segmentation have been reviewed in [4] and [33]. Leveraging deep learning-based image segmentation into SLAM for semantic mapping is also a hot topic. In [172], Li *et al.* combined the LSD-SLAM [16] with CNN-based image segmentation to reconstruct a semi-dense semantic map. Cheng *et al.* [173] integrated a CRF-RNN-based segmentation algorithm with ORB-SLAM [22], and built a dense semantic point-cloud map by using RGB-D data. Deep learning-based semantic



(a) The trajectory generated by ORB-SLAM2 in high-dynamic environment;

(b) The trajectory generated by deep learning methods in a normal environment;

Figure 5. (a): ORB-SLAM2 cannot generate the usable trajectory in high-dynamic environment [170]; (b): The trajectories generated by SfMLearner [32], GeoNet [121] and SC-SfM [171] on the KITTI odometry sequence 09.

segmentation with dense SLAM frameworks have also been applied to construct dense semantic maps. McCormac *et al.* [94] incorporated CNN-based semantic prediction into state-of-the-art dense SLAM method, ElasticFusion [60]. They considered the multi-view segmentation result of the same 3D point and fuse semantic information in a probabilistic manner.

Dynamic scene adaptability: Traditional SLAM relies heavily on static scene assumption, i.e., the performance of SLAM is limited by moving objects, as shown in Fig. 5 (a). The features on static objects are positive to improve the accuracy, while those on dynamic objects have a negative impact on the tracking process. Deep learning-based object detection and semantic segmentation assist SLAM in identifying dynamic objects in the environment to classify the dynamic features. Excellent detection and segmentation networks, such as YOLO [174], SSD [175], Mask-RCNN, [176] and SegNet [177], have been incorporated into traditional SLAM frameworks as an additional thread to identify and eliminate the dynamic features. Zhong *et al.* [178] presented a novel system that integrated SLAM with the object detector SSD, called Detect-SLAM. The SSD was used to detect the dynamic and static objects for every key frame; then, the extracted features on the dynamic objects were removed. Therefore, the robustness and accuracy of SLAM in dynamic scenes were significantly improved. Wang *et al.* [179] considered the effects of moving objects on localization accuracy and constructed maps, and developed a novel SLAM solution. They used YOLOv3 [180] to detect moving objects and constructed a semantic static map with the data without moving objects. Xiao *et al.* [181] developed a new detection thread to detect and remove the dynamic objects, and designed a selective tracking algorithm to process the dynamic features during tracking. Because the object

detection methods are not considered during pixel-level semantic annotation, the classification of feature attributes is not accurate enough. Therefore, Yu *et al.* [182] presented a robust semantic SLAM for dynamic environments with five threads based on ORB-SLAM2. They used SegNet to segment the movable objects at the pixel level and designed a moving consistency check process to detect the movements of the movable ORB features. Only the semantically and geometrically dynamic features were deleted. Bescos *et al.* [183] added moving object segmentation and background inpainting into ORB-SLAM2, thereby achieving outstanding performance in dynamic environments. Recently, Cui *et al.* [170] combined the results of semantic segmentation from SegNet with ORB-SLAM2. They proposed a new method, called Semantic Optical Flow (SOF), to improve the detection of dynamic features.

Scale recovery and assisting localization: Semantic information has also shown its effectiveness in scale recovery and assisting localization. Frost *et al.* [184] represented objects in the environment as spheres and recovered the scale from the detected objects with a known radius. Similarly, in [185], Sucar *et al.* recovered the scale by setting the prior height of the object (car). A detection method was used to detect this object and compute the height, and the scale was solved by the ratio of the calculated height to the prior height. For localization, Stenborg *et al.* [186] proposed a novel method that locates the camera based on semantically segmented images, which is different from traditional localization methods based on features. To obtain more accurate localization, Bowman *et al.* [187] first integrated the geometric, semantic, and IMU information into a single optimization framework. Lianos *et al.* [188] utilized the semantic information of the scenes to establish mid-term constraints in the tracking process, thereby reducing the monocular drift in VO.

3. Autonomous Decision-Making

After perceiving the surroundings and state, autonomous robots will plan appropriate trajectories according to the missions as well as their own state and environment information. A survey of motion and control planning for autonomous vehicles is proposed in [8]. This section briefly reviews the basic algorithms on motion planning and navigation of autonomous systems. We mainly focus on the navigation based on reinforcement learning.

3.1. Planning the motion

The motion planning problem can be divided into two levels: path planning and trajectory planning.

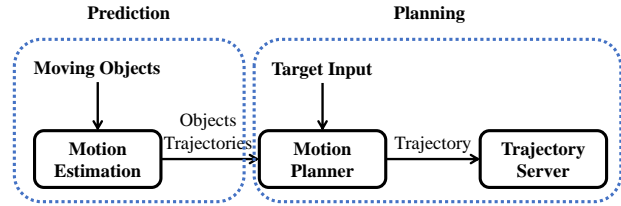


Figure 6. System overview of trajectory planning in a dynamic environment [192].

3.1.1 Path planning

In path planning, the dynamics of the robots need not be considered. It can usually be considered planning the motion of a particle. Path planning algorithms mainly include the following types: artificial potential field (APF) [189], intelligence algorithm [190] and geometric search algorithm [191].

Artificial potential field: Khatib *et al.* [24] first proposed the APF in 1985 for solving the obstacle avoidance problem of mechanical arms. This method was then migrated to the area of robot navigation and global path planning [189]. A potential function was designed to construct a virtual force field, so that the path was planned by tracing the motion of the particle between the initial and final position under the influence of the potential field.

Although the principle of APF is simple and easy to construct, it is easy but dangerous to fall into a local optimum [189]. For example, if the gravitational and repulsive forces of some points in the space are balanced, it will cause the robot to stop at these points or oscillate nearby, resulting in the failure of path planning. Therefore, Ge *et al.* [193] proposed a new repulsive potential function to adjust the distribution of repulsion generated by obstacles. The novel function introduces a regulator manner and effectively solved the local minimum problem: goals nonreachable with obstacles nearby (GNRON). In [194], Mabrouk *et al.* tried to solve the GNRON problem by state optimization. The potential field of robots is manipulated by the internal state so that the local equilibria can be transformed from stable to unstable ones, which effectively avoids GNRON.

Intelligence algorithms: With the development of intelligence algorithms, evolutionary algorithms, genetic algorithms, particle swarm optimization, etc. are gradually used in the research of path planning. The ant colony algorithm directly converts the solution of the target problem to the simulation of the biological search path method. Zhou *et al.* [190] applied the ant colony algorithm to search the optimal path from all feasible paths generated by Voronoi weighted direction diagram. The multi-colony ant optimization algorithm was then presented in [195] for UAV path planning, where the information exchanged among several ant

colonies was used to improve the computing speed. Differently, the path planning method based on the genetic algorithm [196], ant colony algorithm [190] or particle swarm optimization considers the path planning problem as an optimization process. Cheng *et al.* [197] proposed a novel path planning method based on the immune genetic algorithm (IGA), which improves the convergence speed and premature convergence of genetic algorithm. In [198], Bao *et al.* used the particle swarm optimization (PSO) to compute the optimal solution of a reconnaissance path. Although intelligence algorithms are able to perform a global search, there are still some problems, such as premature convergence, complicated calculation, long time consuming and poor real-time performance need to be solved [199]. Inspired by PSO, the gravitational search algorithm (GSA) was improved and used in [200] for path planning, which effectively improved the quality of path.

Geometric search algorithms: Geometric search algorithms can also be divided into random and deterministic search. Random search is represented by probabilistic roadmaps (PRM) [191] or rapidly-exploring random trees (RRT) [201]. A search tree or map is generated by constantly sampling random points in the environment, and then used to search the shortest path. RRT and PRM have fast search speeds, but due to random generation of sampling points, the final path may not be optimal. Hence, Karaman *et al.* [202] changed the selection method of sampling points by introducing a novel cost function, and the proposed algorithm called PRM* and RRT* are asymptotically optimal. Deterministic search was represented by A* [203] and Dijkstra [204], where the search space is formed by uniform discretization environment and the search direction is determined according to the cost function size of the current search node. In order to address the problem of excessive search time, Likhachev *et al.* [205] proposed an anytime heuristic search by incorporating anytime algorithms into A*. Inspired by APF, Dong *et al.* [206] introduced the virtual force into the A* algorithm, and the optimal trajectory planning of UAV was carried out by leveraging the advantages of the two algorithms. Deterministic search can ensure the completeness and optimality of the search while the search range of the algorithm is larger with a longer search time.

3.1.2 Static trajectory planning

The main difference between path planning and trajectory planning is whether the dynamics of mobile robots is considered. Trajectory planning algorithms mainly involve the following approaches: motion primitives-based methods [13], optimization-based methods [207], and path planning-based methods [208].

Motion primitives based methods: These methods

firstly calculate a set of control rate, which is required for a robot to reach a set of states in a short time based on the robot's dynamics, and then the trajectory is obtained based on the calculated control rate and the dynamics of the robot. The motion primitives-based method were proposed by Frazzoli *et al.* [13] in 2005. Its goal is to reduce the complexity of a nonlinear controller design by quantifying the control rate and trajectory. Following [13], Paranjape *et al.* [209] presented two families of motion primitives for enabling fast and agile flight. This method determines the motion primitives and trajectories by sampling path points in the visible area, and the final trajectory is determined according to the cost function of time and the distance between the trajectory and the obstacle. In [210], a novel motion primitive method based on the optimal control algorithm was proposed for global trajectory planning, which can directly generate the trajectories satisfying the dynamics and obtain the control rate, thereby simplifying the controller design. However, its performance is limited by the density of selected motion primitives.

Optimization-based methods: The optimization-based methods regard the trajectory planning as a constrained optimization problem with minimal time or energy. Cowling *et al.* [207] first proposed a method to solve trajectory planning by polynomial fitting. On this basis, in order to make the UAV complete the specified action, Mellinger *et al.* [211] designed a flight corridor to constrain the flightable space, and constructed the trajectory generation problem as the quadratic programming problem of minimum snap control. The optimization-based method can generate the optimal or suboptimal trajectory which meets the performance indicators but with long calculation time.

Path planning-based methods: The path planning-based methods reduce the computation time and improve the efficiency of trajectory planning by searching and optimizing the results of path planning. Furthermore, because the solution starts from a better initial value during planning, this method also achieves better performance. Boeuf *et al.* [208] presented a local trajectory planner with the bi-directional RRT algorithm, and the fourth order spline was used to predict the optimal control rate. In [212], the RRT* was also used for trajectory planning, and the optimal flight trajectory was solved by constructing an unconstrained quadratic planning problem for polynomial trajectories, thereby achieving higher speed of generation. In order to simplify the optimization steps, Gao *et al.* [213] proposed a novel method that utilizes the Bézier curves to represent trajectories and the curves' property was used to construct the convex optimization problem. In addition, they defined a velocity map for robots to navigate in static environments, so that they could obtain the time necessary to reach each point on the trajectory.

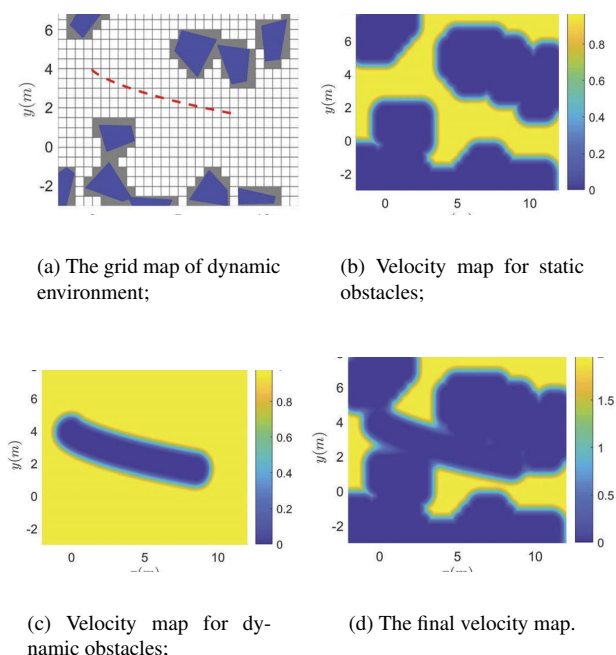


Figure 7. Example of velocity map generation in a dynamic environment [214]. The red dashed line denotes a predicted trajectory of a non-cooperative agent in (a).

3.1.3 Dynamic trajectory planning

Most of the above works are based on the static scenario assumption, while in dynamic scenarios, especially those involving non-cooperative agents, these scenarios are more uncertain and difficult for path and trajectory planning. The cooperative control of multi-agents in dynamic or networked scenarios was discussed and reviewed in [215–223], and we only review here the methods for trajectory planning in dynamic environments. As shown in Fig. 6, the trajectories of moving objects should be predicted before planning the robot’s trajectory to avoid collision. Qian *et al.* [224] considered the dynamic obstacles in the environment and presented a novel path planning algorithm combining APF and improved rolling plan (RP). The obstacles are assumed to move at a constant speed. The local minimum problem is solved by rolling optimization, and their method realize a dynamic obstacle avoidance of the UAV. Trajectory planning in dynamic scenes is mainly carried out through re-planning on existing path planning. Oleynikova *et al.* [225] carried out the initial path planning result by RRT* algorithm and constructed the trajectory planning as a quadratic programming problem, so as to replan in real time according to the dynamic obstacles. Similarly, Usenko *et al.* [226] also modeled the trajectory reprogramming as an unconstrained quadratic programming problem. The main difference is that they represented trajectories by B-spline

curves, which have the advantages of piecewise processing, faster computation speed, and less computer memory consumption. Since the previous methods based on quadratic programming did not take into account the trajectory of dynamic obstacles during trajectory planning, which means that detection and avoidance can only be performed when the non-cooperative agents are very close. Therefore, if the non-cooperative agents move fast, these obstacle avoidance algorithms based on quadratic programming are unable to achieve timely trajectory planning and obstacle avoidance. The best solution to this problem is to introduce the predicted localization information of the non-cooperative agents. Mellinger *et al.* [227] utilized the mixed-integer quadratic program (MIQP) to avoid static obstacles and prevented collision in the UAV group. In [192], the authors proposed an optimization-based framework to solve trajectory generation, and the trajectories of non-cooperative moving obstacles were considered and added to the security constraint. However, the trajectories of non-cooperative obstacles are predicted by the fitted polynomial and constrained by quadratic constraints, which make the problem a non-convex quadratic program (QP). Hence, our previous work [214] utilized the least square method in generating the trajectories of non-cooperative agents. We combined the Bézier curve and safe flight corridor for UAV trajectory planning in dynamic scenes, which makes the problem convex QP. Meanwhile, a novel velocity map similar to [213] was proposed and extended to dynamic environment [214].

3.2. Reinforcement learning based navigation

Navigation can be defined as a process of accurately determining one’s location, planning and following a route from one place to another. With the help of advanced sensors and navigation algorithms, vision has been introduced into navigation [228], [229]. Vision-based navigation leads to wider researches and provides many different solutions in the fields of vision and control. Traditional visual navigation of mobile robots is generally based on three main methods: map-based navigation, map-building-based navigation, and mapless navigation [230]. Map-based navigation requires the global map of the current environment to make decisions for navigation. For example, in [231], the robot used a generic map to accomplish symbolic navigation. Specifically, the robot was not guided to the locations with specific coordinates but with symbolic commands. Symbolic commands are the general description of the types of entities in the environment. In map-building based navigation, robots use different sensors to perceive the environment and update the map. In [232], the robot was equipped with a stereo vision sensor and allowed to explore and map an unknown environment simultaneously. A Rao-Blackwellized particle filter (RBPF) is used to map 3D point landmarks precisely to solve the SLAM problem.

In mapless navigation, the robots do not have any environment information and navigate with the perceived information without maps. Saeedi *et al.* [233] presented a general-purpose 3-D trajectory-tracking system. This system could be applied to unknown indoor and outdoor environments without the need of mapping the scene, odometry or the sensors other than vision sensors.

Reinforcement learning based navigation has been preliminarily studied recently because reinforcement learning is suitable for continuous decision-making tasks in complex environments; it is also a good method for robot problems. Jaradat *et al.* [234] used Q-learning to solve the problem of mobile robot navigating in an unknown dynamic environment. Owing to the infinite number of states in a dynamic environment, the authors limited the number of states based on a new definition of the state space to ensure that the navigation speed is improved. Bruce *et al.* [36] introduced a reinforcement learning method to map-building based navigation. They employed interactive replay for a single traversal of the real environment to build the map and guided a mobile robot to a fixed target in the environment using SLAM techniques without involving humans. In the navigation process, pre-trained visual features and random observations are used to expand the training set. Therefore, the robot can successfully navigate without the need for fine-tuning under environment changes.

During the training period, adding auxiliary tasks, such as value function [235], reward prediction [236], and map reconstruction [237], can improve the reinforcement learning efficiency. Jaderberg *et al.* [236] proposed a novel unsupervised reinforcement and auxiliary learning algorithm. To enhance the standard reinforcement learning method, the algorithm predicted and controlled the features of the sensorimotor stream by treating them as pseudo-rewards for reinforcement learning. Moreover, during the training process, the agent was allowed to perform additional tasks, such as pixel control, reward prediction and value function replay. In [237], the agent only used the visual information (images of the monocular camera) for navigation search (finding the apple in the maze). The study considered two auxiliary tasks. In the first task, a low-dimensional depth map was reconstructed at each time step, which is beneficial for obstacle avoidance and short-term path planning. The other task involved loopback detection, wherein the agent learned to detect whether the current location had been visited within the currently running trajectory. The experiments in these studies prove that co-training can significantly improve the training speed and performance of the model.

Recently, multi-modal reinforcement learning has become a hot point and cutting edge, which combines multi-modal information, such as language and video, with vision as inputs in the reinforcement learning model. To deal with navigation issues, visual language navigation (VLN) [238]

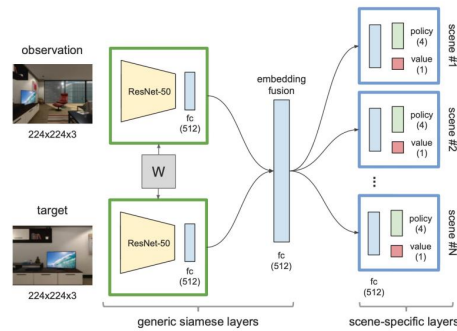


Figure 8. Network architecture of actor-critic deep reinforcement learning mode. [240]. The model takes the current observation image and the target image as inputs to generate an action as output in a 3D simulation environment. The goal is to learn how to navigate to different targets in a scene without retraining.

has been widely used in recent years. VLN is a task that guides the embedded agent to execute natural language instructions in a real 3D environment. It requires a deep understanding of the linguistic semantics, visual perception, and most importantly, the alignment of the two. Wang *et al.* [239] studied how to solve the three key challenges of VLN, namely cross-modal grounding, ill-posed feedback, and the generalization problems. In response to the first and second challenges, the authors proposed the reinforced cross-modal matching (RCM) method, which used reinforcement learning to connect local and global scenarios. In response to the third challenge, self-supervised imitation learning (SIL) was proposed, which helped the agent to get better policies by imitating its best performance from the past.

However, reinforcement learning-based navigation is limited to a small action space and sample space, and it is generally in a discrete situation. Moreover, more complex tasks closer to the actual situation often have a large state space and continuous action space.

Deep reinforcement learning based navigation has achieved promising results recently by combining the perceptual ability of deep learning with the decision-making ability of reinforcement learning. Deep learning methods equip robots with the ability to learn high-dimensional data [241] to ensure that they can accomplish more complex tasks, as shown in Fig. 8. By using deep reinforcement learning methods, agents can automatically learn the characteristics of the data collected by the sensors without human intervention. Moreover, agents can formulate a navigation policy to ensure navigation in more complex environments, especially in real world. In the field of navigation that is biased toward obstacle avoidance, the methods used in [242, 243] obtained satisfactory generalization performance. Therefore, the models trained solely in virtual environments can be directly transferred to real robots. Chen *et al.* [242] presented a novel approach to train ac-

tion policies to acquire navigation skills for wheel-legged robots using deep reinforcement learning. Moreover, domain randomization increases the diversity in training samples, improves the generalization ability, and focuses on the task-related aspects of observation. Therefore, it has been used in real environments with more complicated types of obstacles and movements. Xie *et al.* [243] proposed a new network structure, consisting of two parts, to deal with the obstacle avoidance problems. First, the convolutional residual network was used to extract the depth information. Then the reinforcement learning structure, called dueling architecture, only used a monocular RGB vision as input. The structure could efficiently learn how to avoid obstacles in a simulator even with very noisy depth information predicted from the RGB images.

Deep reinforcement learning algorithms can be divided into two types: value-based and policy-based. Value-based algorithms learn the value function or the approximation of the value function, and then select a policy based on the value. The Deep Q-Network (DQN) is the first value-based algorithm. Tai *et al.* [244] first proposed a method that used raw sensor information to build an exploring policy for robotics based on deep reinforcement learning. Specifically, the reinforcement learning method based on the DQN was used to explore a corridor environment with the depth information from an RGB-D sensor. Lample *et al.* [245] played a shooting game through deep reinforcement learning, which used the same auxiliary tasks as in [236]. The novelty resides in that the authors introduced the DQN to co-train with the game features, which was found to be critical in guiding the convolutional layers of the network to detect enemies. The original DQN can only be applied in tasks with a discrete action space. For an extension to continuous control, many policy-based algorithms have been formulated. Policy-based algorithms learn directly based on the policy without the reward. Deep deterministic policy gradients (DDPG) [246] and normalized advantage function (NAF) [247] are policy-based algorithms that have been widely used. In comparison to NAF, DDPG needs less training parameters. Tai *et al.* [248] presented a model that uses asynchronous multithreading DDPG to collect data. It helped in improving the sampling efficiency. The mapless motion planner can be trained end-to-end without any features designed by humans or prior demonstrations.

The actor-critic (AC) algorithm [249] combines two types of deep reinforcement learning algorithms mentioned above. That is, the actor network chooses the proper action in a continuous action space, while the critic network implements single-step-update, which improves the learning efficiency. In other words, it learns both the value function and policy function. The Asynchronous Advantage Actor-Critic (A3C) network is an improvement of the AC network [250]. It uses the multi-threading method. The A3C network per-

forms interactive learning with the environment in multiple threads simultaneously, thereby avoiding over-fitting of the training data. Zhu *et al.* [251] took both the target and scene images as inputs of the deep reinforcement learning network; then, the agent followed the output action to navigate to a target. During the training process, a new observation was valued through the A3C network to ensure the agent does not need to retrain the new target. In [250], the authors combined the A3C network with a cutting-edge exploration to learn effective exploration policies based on the state of high-dimensional robots. Therefore, robots can autonomously explore the unknown cluttered environments. During the navigation process, robots maximize the total gain along the navigation path.

With the developments in deep reinforcement learning algorithms, the problem of vanishing gradient arises. That is, as the number of hidden layers in neural networks increases, the classification accuracy in the training process decreases. LSTM architectures [252] can tackle this problem. When the input data is time-varying, LSTM structures can capture the long-term dependencies of sequential data. Mnih *et al.* [250] use LSTM units to reach better decisions by considering the previous state characteristics. With the same purpose, in [237], the authors combined the LSTM structure with auxiliary tasks and the A3C networks to navigate in a maze to find a target using the images of the monocular camera. In real word navigation, training data are more variable and unpredictable than those in simulation experiments. Therefore, LSTM structures play a vital role in generating good navigation policies. Mirowski *et al.* [253] only used the visual information as input for unmanned vehicle navigation without relying on maps, GPS, and other assistant methods. The authors put unmanned vehicles in complex scenes of city scale and collected real-world data for training. To accomplish the tasks, a multi-city navigation network with LSTM structure was proposed. The method processed images, extracted features, remembered and understood the environment, and finally generated the navigation policies.

To improve the performance of the deep reinforcement learning networks, training data should be essentially considered in experiments. Sufficient and variable training data are the basis of convincing results during the training process, while in the real world, data are always unobtainable or missing. To solve this problem, simulation frameworks can be utilized to train agents. In [251], the first simulation framework, called AI2-THOR (The House Of inteR-actions), was developed that provided an environment with high-quality 3D scenes as well as physics engines. Therefore, the robot in a simulation environment can effectively collect several training samples, which improves the utilization efficiency of the data. Wortsman *et al.* [254] also used the AI2-THOR framework in experiments, providing

indoor 3D synthetic scenes in four room categories, including kitchen, living room, bedroom, and bathroom. A certain number of scenes of each type can be chosen as the training data. Another way to get more training data is to integrate the training process with real as well as synthetic environments, because obtaining synthetic training data is much easier and cheaper than real data. For example, owing to the differences in environmental characterization and residential planning between real and synthetic environments, Zhu *et al.* [240] proposed a joint framework, i.e., the joint reinforcement transfer (JRT), to jointly adapt the visual representation and policy behavior. Moreover, the framework utilized the interactions between the environment and policy. Specifically, the visual features were transferred from the synthetic domain to the real domain to ensure that the knowledge learned from the synthetic environment can be adopted directly without changing the policy function. The adversarial loss was used to supervise the transfer training process. Adversarial learning is another way to improve the generalization ability. Tang *et al.* [255] proposed AdaTransform, which combines reinforcement learning and adversarial learning to form meta-transformations by jointly optimizing the triplet network online to learn bidirectional data conversion. During the training phase, it performs competitive tasks to increase data differences and reduce overfitting. During the testing phase, AdaTransform performs collaborative tasks to reduce data differences and improve deployment. Ultimately, large transformation spaces can be effectively explored with limited domain knowledge.

4. Discussion

4.1. Perception

The constructed map is an intuitive representation of the scene perception and the basis for intelligent robots to autonomously perform advanced tasks. Mapping has undergone a development process *from 2D to 3D, from sparse to dense, and from topological to semantic, among others*. Furthermore, although several methods have been proposed to improve the localization accuracy, there are still many challenges remaining to be solved. Therefore, we summarize the challenges and promising directions of perception as follows.

- **Map reusing:** *The reusable property of maps* is a great challenge, especially the maps built by direct or semi-direct methods. If the map of the current scene is available, robots only need to load the existing model to realize global awareness, which can save several computations. Unlike the maps constructed by feature-based methods whose 3D points are described by descriptors, direct and semi-direct methods describe the map points with only position, which makes it scarcely possible to establish accurate associations between map points and images. Hence, *map reuse, map-based relocalization and loop detection* are challenges for direct and semi-direct methods, and their combinations with deep learning to solve these problems will be a promising direction.
- **Mapping in large scale environments:** The accuracy and details of a map conflict with the amount of storage it occupies, and different tasks require different types of maps. However, mapping in large scale environments incurs serious scale-drift problems. Therefore, *mapping in large scale environments* is a problem for SLAM to be solved. It will also be a challenge to make the robot autonomously choose the most suitable map according to its task.
- **Consistency mapping in different scenarios:** The same map representation under different conditions in the same scene is also a problem to be solved. Humans can accurately identify the same place in *different seasons, different weather, and other conditions*, which is not yet possible for current autonomous systems. Therefore, assigning different features, especially high-level features based on deep learning, such as *semantic information and text information*, will be helpful for robust perception and presentation.
- **Geometric prior assist in map:** Utilizing *traditional geometric prior* in scale information recovery of mapping is helpful and a promising direction with broad development prospects. For example, semantic labels predicted by deep learning are used to correlate with the *knowledge graph* of objects to obtain prior geometric information; therefore, the detailed scale, structure, and 3D information can be obtained.
- **Accurate localization and mapping in complex scenarios:** The accurate localization and mapping in *low light, high dynamic scenes, cross-season, complex weather, etc.* Researchers have conducted some studies on these topics by combining deep learning and made some progress, but the robustness and accuracy are not sufficiently compared with the traditional methods.
- **Represent the environment based on deep learning:** *Representing the environment based on deep learning* is another challenge and a promising direction. Although previous works such as [157–159] leveraged the deep learning into mapping, the maps of these methods are still built traditionally.
- **Multi-sensor data fusion based on deep learning:** Fusing information from *multi-sensors (IMU, LiDAR, event-based camera, or infrared camera)* or multi-agent is an effective way to deal with poor quality input

images comprising motion blur and recover scale information. However, expressing the additional sensor information explicitly in the loss function is a significantly challenge. For example, the current methods leverage IMU data with images for pose estimation in a supervised manner [130, 131], and the information from IMU is not represented in the loss function. Thus, whether the IMU data plays an important role in pose estimation and what role it plays is unknown and not yet explainable.

- **Localization with deep learning:** Deep learning-based visual odometry lacks *the mapping process*, which limits the in-depth perception of autonomous systems to the environment and affects the subsequent decision-making. In addition, combining the deep learning methods with traditional SLAM is a promising direction. Compared with combining depth estimation networks, pose regression networks have fewer parameters and better real-time performance, which make them more suitable for incorporating into the traditional SLAM frameworks.
- **Localization based on deep learning:** Solving localization with deep neural networks is a hot topic, and supervised methods have achieved outstanding results [129]. However, effectively solving the *training data* problem is still a challenge. Moreover, although unsupervised methods do not require ground truth during training, there is still much room for improvement in *accuracy and transferability*.
- **Scale consistency estimation based on deep learning:** This is another important challenge for deep learning-based tracking. The ability of *generating full trajectories* over a long video sequence is still far from that of conventional methods. Especially, the pose network trained by a monocular video is not sufficient to generate complete trajectories due to the per-frame scale ambiguity, as shown in Fig. 5 (b). Although Bian *et al.* [171] proposed a novel loss function to constrain the scale consistency, it is still far from the real trajectory.
- **Accuracy VS real-time performance via deep learning:** The accuracy of depth and pose prediction can be improved by utilizing *multi-task, multi-view, or novel neural network frameworks*. Learning more geometric details from multiple views or other tasks can greatly improve the pose and depth estimation accuracy. From Table 2, we also find that the combination of multi-tasks (such as semantic, motion segmentation, and optical flow) is the development trend of perception. Previous works have proven that complex network structures are beneficial for improving the net-

work performance. However, complex networks will result in a huge number of parameters, and the application of deep neural networks have a higher demand on the *computing power* of the systems, which limits the practical applications and impacts the real-time performance. Therefore, using novel learning architectures, such as *light weight network and knowledge distillation*, to improve the real-time performance of pose and depth prediction networks will be another trend.

4.2. Decision-making

Trajectory planning: Although trajectory planning has developed over the past 60 years, with the increasing demands in tasks, traditional trajectory planning still faces many problems.

- **State estimation of agents in noisy environment:** The existing algorithms are designed under the assumption that the observation information is accurate, but there must be some errors in the actual estimation value. The accuracy of the trajectory predictions of non-cooperative agents can be improved by observing the non-cooperative agents via observations from multiple teammates, i.e., we can borrow the idea of distributed estimation to improve the estimation performance.
- **Planning in high dynamic scenes with multiple non-cooperative agents:** Trajectory planning in a high dynamic scene is still a challenging problem, especially under the scenario of *multiple non-cooperative agents in high dynamic scenes*. The accurate prediction of the trajectories of these non-cooperate agents is important and challenging for trajectory planning, especially considering the uncertainty of the movements of non-cooperative agents.
- **Understanding the intention of non-cooperative agents:** Improving the accuracy of trajectory prediction by using the cognition of non-cooperative agents is also a promising direction, which has been a largely under-explored domain. For example, analyzing the intentions of non-cooperative agents,(whether they are hostile to our intelligent robots) and predicting their next movement through their intentions are challenging problems.
- **Multi-agents and multi-tasks:** Multiple tasks or complex tasks can be accomplished effectively by the collaboration of multiple agents. The *autonomous cooperation and task allocation in multi-agents with multi-tasks* are also an important problem to be solved. It is a development direction for autonomous systems to realize the optimal strategy for task assignment ac-

ording to the current state of robots and task requirements.

Reinforcement learning: Significantly developments are required before reinforcement learning can be applied to autonomous systems. There are many challenges to be solved.

- **Sparse rewards:** Rewards have a great impact on the learning results during the training process, but the problem of *sparse rewards* in reinforcement learning has not been well solved. When the training tasks are complicated, the probability of exploring the target (getting positive rewards) by random methods becomes very low. Therefore, it is difficult for the reinforcement learning algorithms to converge by only relying on the positive rewards. To deal with this problem, designing the reward function using another method will be helpful in avoiding the problem of *sparse rewards*, improve the training efficiency, and final performance.
- **Performance in real world:** Due to the differences between simulation environments and real scenes, many reinforcement learning algorithms with higher performance in simulation experiments cannot handle the practical problems in real world. This strongly limits the widespread application of this technology. Moreover, reinforcement learning models require thousands of trials and errors to train iteratively, while in real world, agents can hardly withstand so many trials and errors. Establishing the network that can be directly transferred to real world is a resolution, which can translate the virtual scenes generated in the virtual simulator into real scenes for reinforcement learning training.
- **Transferable property improvement:** In many tasks, the training data are limited and unacquirable. *Adversarial learning (GAN)* can be applied to increase the data differences in the training process and reduce data differences in the testing process, which improves the data diversity and the generalization ability of the model. Moreover, many transfer learning methods, such as *one-shot learning*, *few-shot learning*, and *meta learning*, can recognize the model and apply the knowledge and skills learned in previous tasks to novel tasks. This is effective for enhancing the transferability, reducing the network parameters, and promoting generalization.
- **Multi-modal and multi-task:** Current reinforcement learning-based navigation methods mainly focus on visual input only; however, by considering the information from multiple models, such as voice, text, and

video, the agents can better understand the scenes and the performance in experiments will be more accurate and convincing. Moreover, it is proved that *multi-task* reinforcement learning models, in which the agent is simultaneously trained with auxiliary and target tasks, improve the training efficiency. Therefore, *multi-task* is also a development trend in navigation based on reinforcement learning.

4.3. Application

The development of autonomous perception and decision-making drives the emergence of a large number of high-tech industries, such as unmanned vehicles and service robots, which have greatly improved the quality of human life [256]. Furthermore, autonomous systems have a broad application prospect in various fields, like industry, agriculture, services, transportation, etc. For example, accidents in petrochemical industry occur from time to time in recent years, which inevitably cause great damage of life and property. The use of autonomous systems to monitor a chemical park can help to find dangers in advance. Intelligent monitoring robots with various gas and optical sensors can monitor the safety hazards in the chemical plant area in real time. Robots autonomously perceive and construct the map of structure environments based on visual sensors. Then, based on the perceived information, robots plan the path and tasks for better monitoring. In case of emergency, the environment becomes semi-structure and complicated, in which autonomous robots can reach dangerous areas, sense the surrounding areas, deliver important information to the staff, assess the situation and even assist staff in decision-making as well as rescue. At present, the difficulties lie in the distance between theoretical research and practical applications, such as reliability, robustness and real-time response capability. Therefore, this survey reviews the existing perception and decision-making methods, which provides a guideline for future research and promotes the development of autonomous systems.

5. Conclusion

Through this review, we aim to contribute to this growing area of research by exploring the perception and decision-making methods of autonomous systems. Therefore, we review the related works of SLAM, trajectory planning and navigation in the learning age. The influx of deep learning algorithms to support the subtasks of SLAM or incorporate with SLAM can be observed in recent works, which improve the robustness and performance of traditional SLAM algorithms. Meanwhile, navigation based on reinforcement learning also provides a new idea for decision-making in autonomous systems. We provide two comprehensive taxonomy tables of state-of-the-art SLAM algorithms as well as deep learning-based depth and pose estimation meth-

ods, which clarify the mainstream algorithm framework and the development trend. Finally, this review highlights the key challenges and promising directions in perception and decision-making.

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