Jin *et al.*
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REVIEW

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A Comprehensive Review of Key Technologies for Robot Motion Planning in Contact Tasks in Industrial Automation Scenarios

Shibo Jin[1], Kaichen Ke[1], Boyang Gao[2], Li Fu[3] and Xingrong Huang[1*]

Abstract
With the swift advancement of industrial automation, robots have emerged as an essential component in emerging industries and high-end equipment, thereby propelling industrial production towards greater intelligence and efficiency. This paper reviews the pivotal technologies for motion planning of robots engaged in contact tasks within industrial automation contexts, encompassing environmental recognition, trajectory generation strategies, and sim-to-real transfer. Environmental recognition technology empowers robots to accurately discern objects and obstacles in their operational environment. Trajectory generation strategies formulate optimal motion paths based on environmental data and task specifications. Sim-to-real transfer is committed to effectively translating strategies from simulated environments to actual production, thereby diminishing the discrepancies between simulation and reality. The article also delves into the application of artificial intelligence in robot motion planning and how embodied intelligence models catalyze the evolution of robotics technology towards enhanced intelligence and automation. The paper concludes with a synthesis of the methodologies addressing this challenge and a perspective on the myriad challenges that warrant attention.

Keywords Industrial automation, Motion planning, Environmental recognition, Trajectory generation, Sim-to-real transfer

1 Introduction

In the contemporary manufacturing landscape, automated production systems integrated with robotic arms have emerged as pivotal to enhancing manufacturing efficiency and product excellence. Tracing the evolution from the onset of the third industrial revolution [1] to the current era characterized by Industry 4.0 [2], robotic technology has consistently been at the heart of industrial automation advancements (as depicted in Figure 1). Within the spectrum of tasks performed by robotic arms, contact-intensive operations such as manipulation, assembly, grinding, and welding (illustrated in Figure 2) are crucial for the realization of automated production processes [3–5]. These operations necessitate that the robot or its end effector engage in sustained and frequent contact with the objects or environments within its interactive domain. This requirement underscores the need for the robot to exhibit a high level of agility and precision, and also to possess the adaptability to navigate the dynamic and ever-evolving production settings and demands [6].

*Correspondence:
Xingrong Huang
huangxingrong@buaa.edu.cn
[1] Sino-French Carbon Neutrality Research Center, Sino-French Engineer School, Beihang University, Beijing 100191, China
[2] Beijing Geometry Robotics Ltd, Beijing 102402, China
[3] UMR5513, Ecole Centrale de Lyon, CNRS, ENTPE, LTDS, 69130 Ecully, France

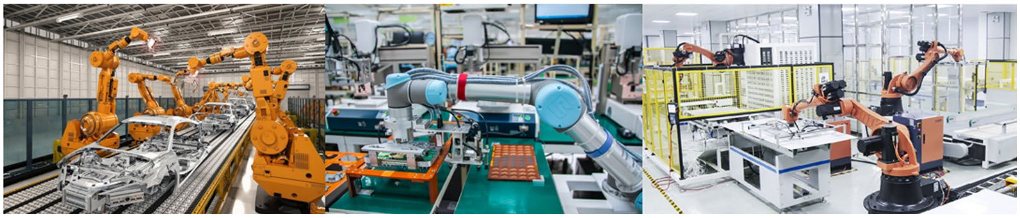

Figure 1 Automated production using robotic arms. Left: car assembly; Center: chip manufacturing; Right: precise assembly

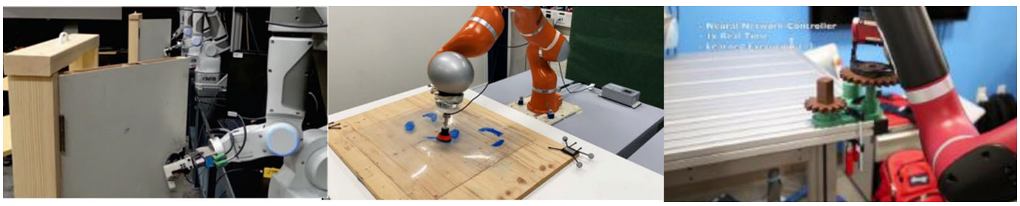

Figure 2 Robots perform a variety of contact tasks [3–5]

The successful execution of these tasks depends not only on the hardware performance of the robot, but also on the intelligence of its software system. With the complexity of production tasks and the diversification of working environments, traditional industrial robots face great challenges in performing these tasks. For instance, during robotic welding operations, accurate control over the welding path is crucial; however, it is equally essential that the system can dynamically adjust welding parameters in real-time to accommodate varying materials and conditions. In such scenarios, the ability to adapt to complex environments, fully comprehend the task at hand, and implement more flexible robot motion planning becomes increasingly valuable and competitive [7]. Conventional motion planning techniques frequently rely on predefined trajectories and parameters, which are inadequate for navigating the intricacies of dynamic production settings. As a result, substantial time investments are required for programming and validation, hindering efficiency and flexibility in robotic manufacturing applications [8]. With the development of artificial intelligence technology, the integration of artificial intelligence into the robotic manufacturing process has been internationally recognized as the main driving force for the transformation of traditional factories and the realization of higher-level automated production [9]. Therefore, making robot motion planning more intelligent while ensuring operational accuracy has become a key focus of current research. For example, Tesla has adopted advanced robot motion planning technology in its automobile manufacturing process, and realized the automatic assembly of body parts by integrating high-precision vision system and intelligent algorithm. The technologies they selected include visual recognition based on deep learning and trajectory planning based on optimization, which not only improves the assembly accuracy, but also significantly shortens the production cycle. The application of this technology not only improves the production efficiency, but also reduces the labor cost and production error, and sets a new benchmark for the automotive industry.

To effectively tackle robot motion planning for contact tasks in industrial automation scenarios, it is essential to conduct comprehensive research in three critical domains: Firstly, environment recognition must be enabled, allowing the robot to accurately perceive and analyze its surroundings, including identifying objects and obstacles, and extracting key features from diverse sensory data. This foundation enables the robot to adapt to complex environments and lay the groundwork for subsequent tasks. Secondly, trajectory generation strategies should be developed, creating optimized motion paths tailored to specific environmental conditions and task demands. These approaches must be flexible and scalable, accommodating varying restrictions and conditions to meet operator needs. Finally, the simulation-to-reality transfer process involves seamlessly translating motion planning strategies from simulated environments to actual production settings, thereby bridging the gap between virtual experiments and real-world deployments. By conducting in-depth research in these three key areas, we ensure that robots can perform tasks more efficiently and safely in actual production environments, thereby promoting the development of industrial automation technology and laying a solid foundation for achieving smarter automated production processes.

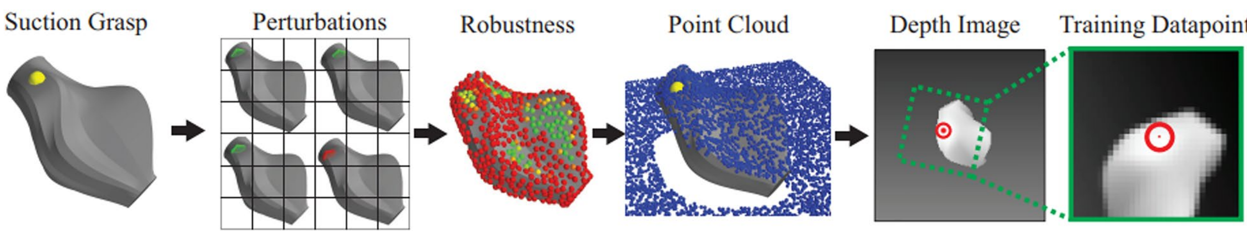

Figure 3 Object identification process utilizing vision-based techniques with Dex-Net [14]

This review delves into the recent advancements in the critical technologies pertaining to motion planning for robots engaged in contact tasks within industrial automation scenarios. It provides a detailed examination of the current challenges and offers insights into prospective development trajectories. Section 2 is dedicated to the challenge of environment recognition, offering an analysis of solutions that leverage both independent modal environmental information and the integration of multi-modal environmental data. Section 3 focuses on trajectory generation strategies, elucidating the evolution from traditional search and optimization-based methods to more sophisticated learning-based approaches, and culminating in the discussion of embodied intelligence models that exhibit enhanced generalization capabilities. Section 4 addresses the sim-to-real transfer challenge, presenting an overview and comparison of prevalent simulation platforms that are instrumental in conducting simulation experiments for robotic contact tasks, along with an exploration of various methodologies designed to bridge the gap between simulation and real-world application. The final section encapsulates the key technologies involved in the trajectory planning process for robots performing contact tasks, accompanied by a discourse on the perspectives and potential directions for future research within this domain. This review mainly focuses on contact tasks, and as far as we know, there are no review articles specifically addressing this issue.

2 Environment Recognition

Environmental recognition is the primary issue that robots must address before performing tasks, involving the perception, understanding, and modeling of the surrounding environment. For contact tasks, the technical challenges comprise identifying objects in real-time amidst dynamically changing environments, predicting the trajectories of obstacles, and ensuring safety during interactions, thereby providing essential reference information for generating precise motions. Environmental recognition necessitates the acquisition of diverse modalities of environmental data, including vision, tactile sensing, auditory cues, thermal feedback, and others. One can leverage a single modality to satisfy the demands of environmental recognition or integrate multiple modalities concurrently to foster a deeper understanding of the environment.

2.1 Related Research Using Independent Modalities

Research into independent modalities predominantly centers on the analysis of data garnered from a single class of sensory input. Within the domain of robotic contact tasks, vision and tactile feedback stand out as the two most extensively utilized modalities. Visual information can provide environmental status information such as target posture and collision, while force and tactile information can ensure the safety and reliability of the robot interaction process.

Through the deployment of computer vision technology, robots can effectively perceive the geometric attributes (shape, color, position) of objects via image analysis, thereby enabling real-time understanding and comprehension of dynamic and complex environments. The synergy between computer vision and robot control constitutes a widely employed approach for addressing interaction challenges in uncertain settings [10]. Taking the grasping task for instance. Levine et al.'s method for learning hand-eye coordination enables robots to generalize from a limited number of visual samples, allowing them to grasp objects from any angle [11]. The incorporation of multiple cameras, as demonstrated by Roth et al., facilitates visual closed-loop control and enhances the precision of robotic object grasping through real-time visual feedback [12]. Beyond these examples, machine learning-based data-driven methods offer greater flexibility and generality in addressing environmental uncertainty, particularly in identifying grasp points for task targets in complex environments. They can achieve high success rates in estimating the grasp pose of objects with varied geometries [13]. The Dex-Net4.0 framework implemented by Mahler et al., contains 5 million synthetic depth images and employs training points in the form illustrated in Figure 3. It achieves an accuracy rate of 95% when predicting the grasping pose of untrained objects [14]. Some studies have also addressed the safety

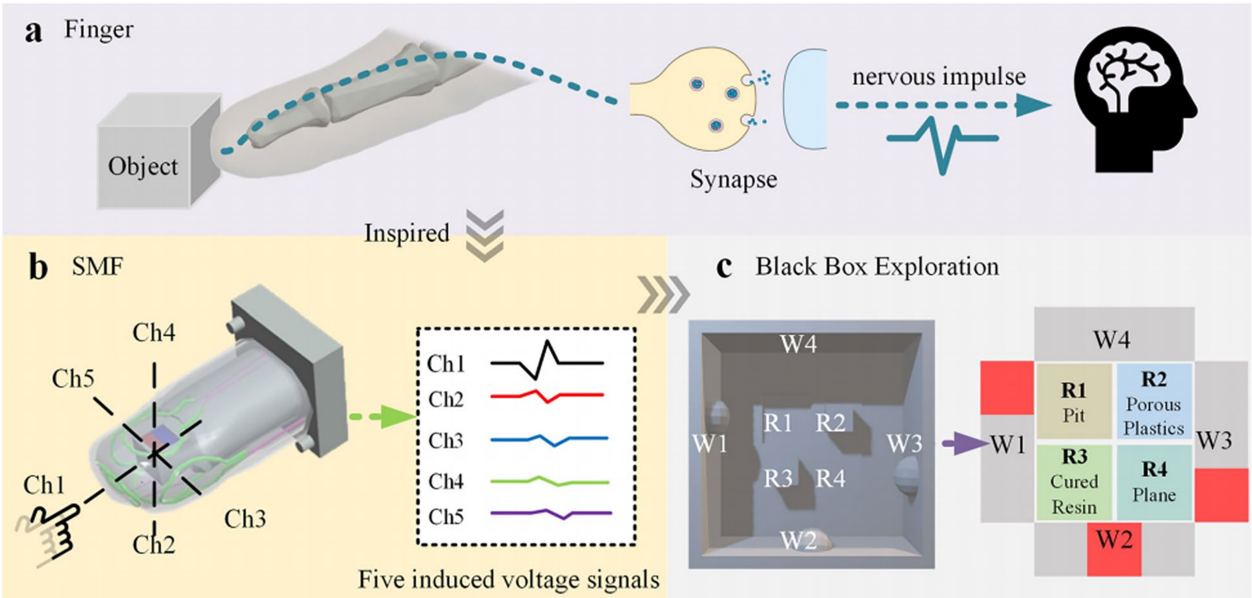

Figure 4 Design of force-tactile sensors inspired by human touch sensitivity [17]

problem for robots participating in production processes using visual modalities. Arents et al. utilize the visual information from human-robot interaction environments to detect people and related objects, thereby enabling task continuation, pause, or termination [7]. These studies demonstrate the pivotal role of visual modality in empowering robots to make informed implementation decisions, optimize actions and continuously adjust their behavior. The capability of extracting features from visual data is particularly crucial for obtaining pose information and distinguishing between working states in contact tasks.

The main role of tactile information in environment recognition tasks is to enable robots to adaptively interact with objects possessing diverse materials and geometries prior to and during contact operations. Current studies focus on acquiring more accurate tactile information and effectively using this information. Several research teams have designed a range of robot actuators equipped with robust tactile perception to obtain precise contact force information [15]. For instance, Yussof et al. developed an optical three-axis sensing system, which leveraged the obtained force information to realize low-force interaction and object surface recognition through control algorithms, thereby preventing damage to the object [16]. Zhang et al. has designed a soft magnetoelectric finger capable of detecting forces in various directions, demonstrating great potential for enhancing the accuracy and flexibility of robot operation (Figure 4) [17]. In tactile information utilization, researchers at McGill University have developed tactile control strategies to maintain grasp stability and make adjustments when objects slide [18]. Walid Amanhoud et al. proposed a force correction model, which adaptively improves the accuracy of force tracking based on radial basis function and reduces the force error to a negligible level [4]. Building upon the obtained force information, Hogan summarized the robot impedance control method, and established a virtual mass-spring-damping dynamic model for the interaction between the robot and the environment. This approach enables robots to exhibit flexible states by adjusting relevant stiffness and damping coefficients during environmental recognition processes, thereby ensuring safe acquisition of environmental information in contact tasks [19]. Ott, Albu Schffer, and the German Aerospace Center (DLR) use impedance control as the core to control the robot's position, velocity, torque, and other dynamic parameters through force sensors at each joint of the robot. This approach is integrated with a 7-degree-of-freedom redundant robot configuration, enabling the design of a lightweight and dexterous robot. Such a robot is capable of achieving human-like force-sensing feedback in interaction tasks [20–23]. All the above studies show that tactile information plays an important role in robot environment recognition tasks, which enables robots to flexibly respond to various contact tasks in complex and dynamic environments, thereby improving their operation accuracy, safety and reliability.

In summary, the utilization of singular modality for environmental recognition entails distinct roles for vision, which encompasses RGB and depth data, and tactile. The integration of these two principal modalities,

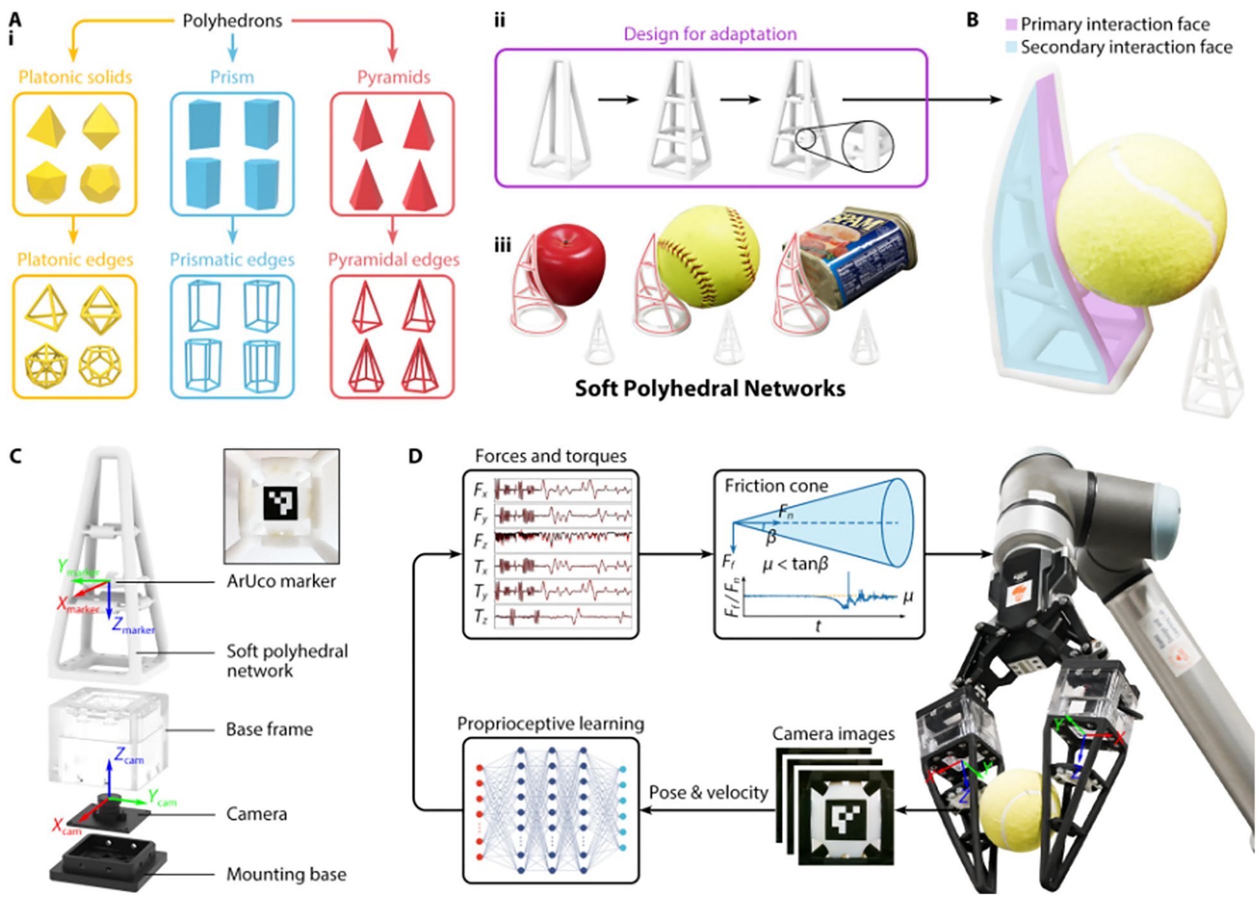

Figure 5 Visuo-tactile sensors designed in GelStereo [29]

along with additional environmental data, has led to significant advancements in multi-modal data fusion technology in recent years.

2.2 Related Research on Using Multimodal Data

Multi-modal data fusion methodologies are designed to amalgamate information harvested from an array of sensory inputs, including but not limited to visual, auditory, and tactile data, with the aim of achieving a more holistic and resilient comprehension of the ambient environment. This synthesis significantly bolsters the robot's capacity to adapt to the fluidity of environmental changes and enhances the precision of task execution. It is accomplished through the accurate extraction of environmental cues and the informed decision-making for action deployment [24].

Firstly, the benefits of fusion between vision and tactile in environment recognition tasks can be leveraged. Notably, research has explored the integration of these two modalities and applied them to robotic tasks. For instance, by integrating vision and tactile, multimodal deep reinforcement learning can be applied to the control of robotic arms to improve their generalization performance, resulting in significantly improved task success rates and operational accuracy in multiple task scenarios [25, 26]. Meanwhile, studies have drawn inspiration from the adaptation mechanisms of animals to multimodal information and applied self-diagnosis mechanisms to robots to improve adaptive ability [27]. Liu et al. have proposed proprioceptive learning technologies that combine vision and tactile. By designing a soft polyhedral network structure and a vision-based miniature motion capture system, the efficacy has been validated in tasks such as tactile perception, grasping, flexible human-robot interaction, and object shape reconstruction through contact [28]. A visual-tactile sensing technology based on binocular vision, named GelStereo, has also been proposed (Figure 5). This technique captures the deformation information of the flexible contact layer through binocular vision system. By integrating different vision algorithms and contact models, high-precision multi-mode tactile perception functions such as contact geometry reconstruction, sliding detection, and dense 3D force measurement can be achieved [29]. These

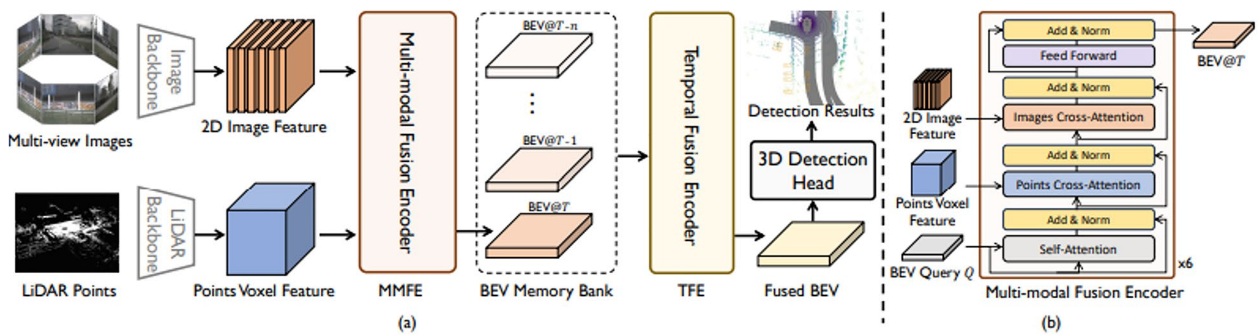

Figure 6 The process of embodied intelligence model processing and learning multi-modal data [35]

studies demonstrate that by integrating the advantages of visual and tactile modality information, the robot can receive more comprehensive environmental information, enhance its discrimination ability when performing contact tasks, and enable it to handle more complex situations.

In addition to the integration of vision and tactile modalities, there have been numerous instances where the fusion of multiple sensory data has significantly enhanced robotic performance. For instance, the synergistic combination of RGB images and 3D point cloud depth information has been exploited to improve the accuracy and robustness of object recognition and localization in complex environments [30]. In the same way, thermal infrared information has been incorporated to improve the object recognition capabilities of robots in industrial settings [31]. Recently, the vigorous development of machine learning has led to a surge in interest in utilizing neural networks for multi-modal fusion and analysis in environmental recognition tasks [32–34]. For example, deformable attention and residual connection structure have been introduced to process multi-modal environmental data through a self-encoding module, thereby mitigating information loss on the 3D object detection task and improve the success rate and adaptability [35].

Furthermore, the advent of large-scale modeling techniques is facilitating a transition from single-modality to multi-modal fusion capabilities. A prime example is the PaLM-E [36], an embodied multi-modal language model developed by Google's research team, which boasts 56.2 billion-parameters and stands as the most extensive vision-language model to date. This model integrates the 54 billion parameter PaLM [37] with 2.2 billion-parameter Vision Transformer (ViT [38]), enabling it to process continuous sensory inputs and cultivate a profound understanding of the environment necessary for executing a variety of robotic tasks, such as retrieving objects from a drawer or performing color classification. Additionally, research teams from Stanford and NVIDIA have engineered the VIMA robot intelligence framework, capable of harnessing a blend of text, image, and video inputs to direct robots in accomplishing designated tasks. This framework has demonstrated learning and zero-shot generalization capabilities [39] (Figure 6), indicating that with ample data support, robots can incrementally develop the ability to analyze and filter environmental objects in accordance with task objectives. This progression paves the way for the realization of end-to-end robot control in the context of environment recognition.

To sum up, when compared to methods employing a single modality, the utilization of multi-modal data fusion significantly enhances a robot's perceptual capabilities, making it the preferred approach for environmental recognition. The integration of artificial intelligence and large-scale model technologies further augments the robot's comprehension abilities, leading to a substantial improvement in environmental recognition performance. This, in turn, provides ample environmental information necessary for subsequent trajectory generation processes (Figure 7).

3 Trajectory Generation Strategy

Trajectory generation is pivotal for the efficient and safe execution of robotic tasks. Central to this research domain are the challenges of devising trajectories that incorporate collision avoidance, optimal timing, and minimal energy expenditure, particularly when navigating dynamic obstacles in complex settings. Trajectory generation strategies can be categorized into traditional search and optimization-based approaches and the more recently emerged learning-based methods [40, 41]. With the progression of large model pre-training technology, embodied intelligence models, which are trained on extensive datasets, have become a focal point for addressing these challenges [42]. These models help improve the ability of robots to adapt to environmental changes and perform tasks accurately, leveraging the experiential

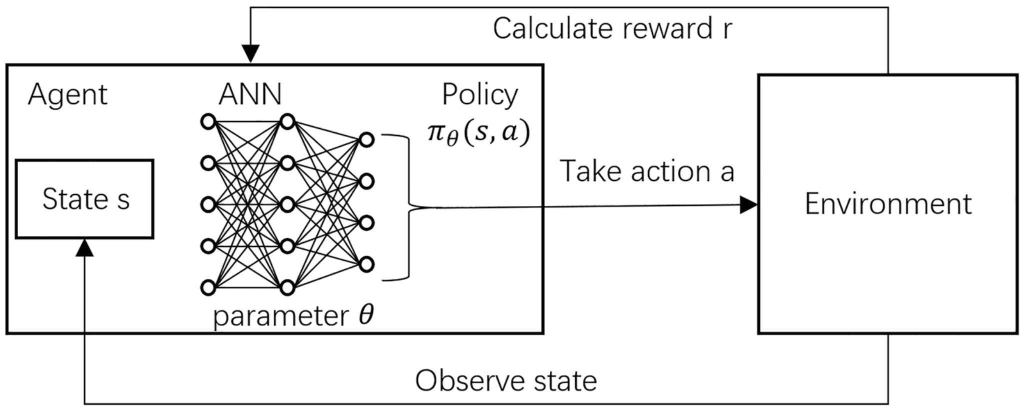

Figure 7 Reinforcement learning theory diagram

advantages brought by massive datasets through data-driven methods [43], which is crucial for accurately extracting environmental information and decision-making processes.

3.1 Trajectory Generation Strategy based on Search and Optimization

The first development in solving trajectory generation problems is the traditional search based method, which divides the space into multiple discrete spatial points, forms a roadmap by establishing connections between the points, and finally relies on graph search algorithms to search for the path to complete the task in the known action space, This paradigm encompasses A* algorithm, Dijkstra algorithm [44], Rapid exploration of Random Trees (RRT) [45], etc. Subsequent studies have built upon these foundational algorithms, incorporating novel heuristics and optimization techniques. For example, the MHA* algorithm [46] has been developed by combining multiple heuristic methods, while the RLHA* heuristic algorithm [47] leverages reinforcement learning to optimized in the search convergence speed. Based on the RRT algorithm, the concept of Artificial Potential Field is integrated, and the search is carried out by gradient descent, which improves the performance in cluttered environments [48]. These algorithms and improvements show that the search-based trajectory generation method has good stability in dealing with simple tasks. It is also convenient for users to control the accuracy of trajectory generation through parameter setting.

The second is the trajectory generation method based on optimization, which abstracts the trajectory generation problem into a mathematical model and transforms it into an optimization problem, so that various optimization problem-solving methods can be used to find the optimal solution, such as the CHOMP algorithm [49] and the TrajOpt algorithm [50]. The CHOMP algorithm takes an optimization by utilizing covariant and functional gradients in joint space to improve the seed trajectory, and TrajOpt adds a penalty for collisions based on it, which can be regarded as a continuous convex optimization process. There are also studies on the local time optimal algorithm based on an optimization method to support the trajectory generation in the case of a mobile robot base [51]. Similarly, for mobile robots, Pan et al. have improved the DWA motion planning algorithm, which improves the safety of the trajectory generated by 50% [52]. The above researches show that the trajectory generation method based on optimization can effectively improve the convergence efficiency by transforming the problem. These methods are suitable for scenarios where reliable trajectories need to be generated quickly.

The search-based method has good performance in trajectory generation accuracy, but its convergence efficiency will be affected by the increase or decrease of the degree of freedom and the degree of spatial dispersion. It is necessary to choose the appropriate algorithm and adjust the parameters according to the actual situation. The method based on optimization can adapt to different degrees of freedom and environmental constraints, and the convergence rate is relatively stable, but the path generated by it is easy to fall into local optimum, and may fail when the global optimal solution needs to be found [40]. Therefore, Ahn et al. have integrated various methods and selected the most appropriate method for trajectory generation according to the complexity of the problem [53]. In general, traditional search and optimization based methods are able to provide efficient solutions in some cases, but may be less efficient in high-dimensional or dynamic environments.

3.2 Learning-based Trajectory Generation Strategies

Machine learning-based methods, especially with the continuous progress of deep learning technology, provide new possibilities for solving the task of trajectory generation. By training the model to learn environmental characteristics and task requirements, more intelligent and adaptable trajectories can be generated [41]. According to the different types of learning algorithms, it can be divided into two types of trajectory generation methods based on reinforcement learning and imitation learning.

Recent advancements in deep learning technology have significantly expanded the capabilities of machine learning-based approaches for trajectory generation. By leveraging complex neural networks to learn environmental characteristics and task requirements, these methods can generate more intelligent and adaptable trajectories [41]. Based on the type of learning algorithm employed, machine learning-based trajectory generation methods can be broadly categorized into two distinct paradigms: reinforcement learning (RL) and imitation learning.

RL-based approaches utilize an agent-environment interaction loop to learn optimal policies through trial and error, with the goal of maximizing a reward signal or minimizing a penalty [54].

Following the setup of the observation space (usually composed of environmental information, such as robot joint Angle, velocity, acceleration and target pose) and action space (next action or trajectory), different reinforcement learning algorithms, can be used for training [55]. Notably, model-free algorithms, such as Proximal Policy Optimization (PPO) [56] and the Actor-Critic (A2C) algorithm [57], have gained widespread adoption due to their efficacy in tackling dynamic and complex problems. These algorithms exhibit superior learning efficiency compared to traditional approaches [58]. The versatility of reinforcement learning has been demonstrated across multiple robot contact tasks, including grasping and manipulation. For instance, the establishment of a Grasp-Q-Network enabled the training of objects with diverse shapes, yielding a remarkable 91.1% grasping accuracy [59]. In similar tasks, researchers employed policy gradient method, and obtained a grasping accuracy of 90.68% [60]. For the item separation task via pushing and pulling, studies using the Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm have led to remarkable results in searching the motion generation strategies [61]. The aforementioned robot contact force information is also employed in reinforcement learning, which markedly enhances sample efficiency and the performance of manipulator operation tasks. This approach effectively facilitates the learning of human grasping processes based on force feedback [62] (Figure 8). Some scholars have proposed a robot arm motion planning method based on deep reinforcement learning. Combining a deep neural network with reinforcement learning, the problem of a robot reaching static or random targets in configuration space is studied. A variety of actor critic algorithms are compared, and suggestions for the use of different algorithms are given [63]. Recently, a reactive 3D optimal motion planning method for actor critical reinforcement learning scheme was proposed, which is suitable for robot motion planning in a complex fluid environment, and take advantage of reinforcement learning method in path planning in complex environment [64]. According to the above studies, this trajectory generation method based on reinforcement learning updates the model through the feedback obtained from continuous interaction with the environment, enabling the robot to adopt to the variation of the dynamic environment during trajectory generation, and exhibit better generalization capacity compared to traditional methods.

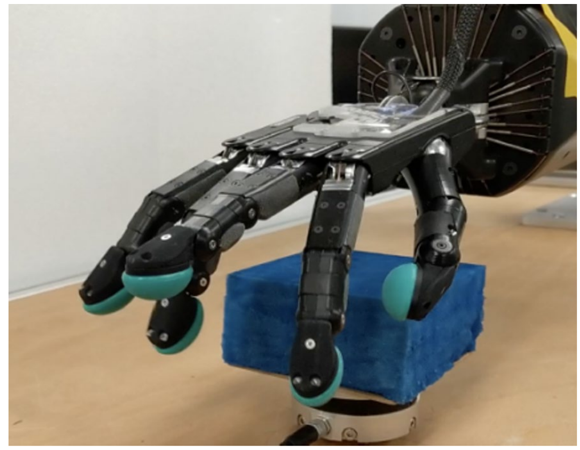

Figure 8 Reinforcement learning-enabled robot hand imitating human grasp based on force feedback [62]

Another trajectory generation method is based on imitation learning, focusing on mimicking expert behavior by learning from demonstrations or trajectories generated by human operators [65] (Figure 9).

Expert data can be obtained in various ways, such as directly using a teaching pendant, motion capture, or indirectly using VR/AR technology to obtain virtual actions [66]. Since imitation learning mainly focuses on learning the correspondence between states and actions/trajectories, the coverage of expert actions on the task space is essential for the learning accuracy. For example, in the context of grasping tasks demonstrated within a virtual environment, researchers have expanded the sampling pool to 100000 grasping samples, yielding a success rate of 74% in real-world grasping scenarios following imitation learning [67]. Recently, a new framework combining motion planning and imitation learning is proposed, which combines the imitation learning method of behavior cloning and inverse reinforcement learning to effectively improve the performance of robot motion

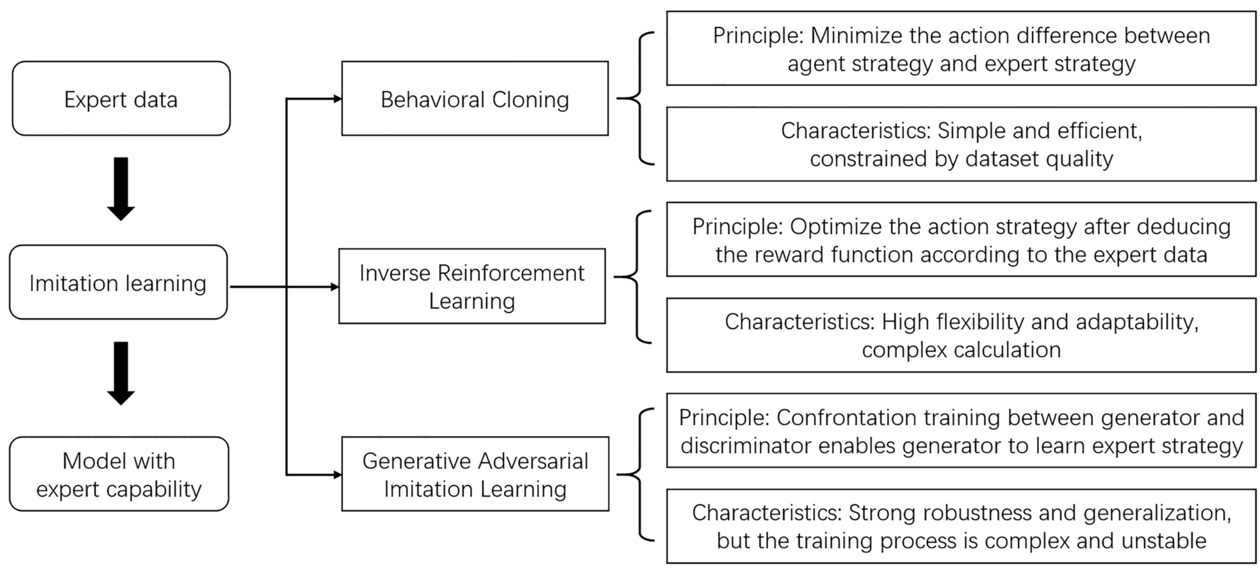

Figure 9 General process of manipulator motion planner based on imitation learning

planning in a complex environment. The effectiveness of the framework is verified by experiments, and its application potential in different tasks is demonstrated [68]. When we accumulate enough expert data, the imitation method can give full play to the fitting ability of the neural network, quickly establishing the relationships between the environmental information and the ideal actions or trajectories, and making the learning process efficiently.

However, both types of trajectory generation methods have their own inherent limitations. Reinforcement learning methods require a large amount of data and training resources to support the trial and error process [69]. Imitation learning is limited by the quality and quantity of training data. It is also challenging to surpass the performance of the expert behavior. Moreover, the coverage of the expert data seriously affects the final learning outcome in dynamic scenes with high degrees of freedom. In light of these limitations, researchers have combined the two methods: initially training neural networks to acquire basic expert capabilities via imitation learning, and subsequently employing reinforcement learning to persistently experiment, trial, and learn. This hybrid approach effectively addresses the issue of data insufficiency for tasks in complex environments [70]. The advantages and disadvantages of the four trajectory generation methods mentioned above are shown in Table 1, providing a basis for selecting the appropriate method according to the complexity of the contact task, the uncertainty of the environment, the number of robot degrees of freedom and the corresponding limitations.

3.3 Trajectory Generation Strategy based on Embodied Intelligence Model

The embodied intelligence model is a system that can simulate more complex and realistic robot behaviors by

Table 1 Comparative analysis of trajectory generation method

Category	Method	Complexity handling	Dynamic environment adaptability	Degrees of freedom compatibility	Limitations
Traditional trajectory generation strategy	Search-based method	Medium	Medium	Medium	Susceptibility to instability in convergence
	Optimization-based method	High	High	High	Challenged by the elusiveness of global optimality
Emerging Trajectory Generation strategy	Reinforcement Learning-based Method	High	High	High	Mandated by data intensity and computational power requirements
	Imitation Learning-based Method	Medium	Medium	Medium	Dependent on an extensive corpus of expert demonstrations

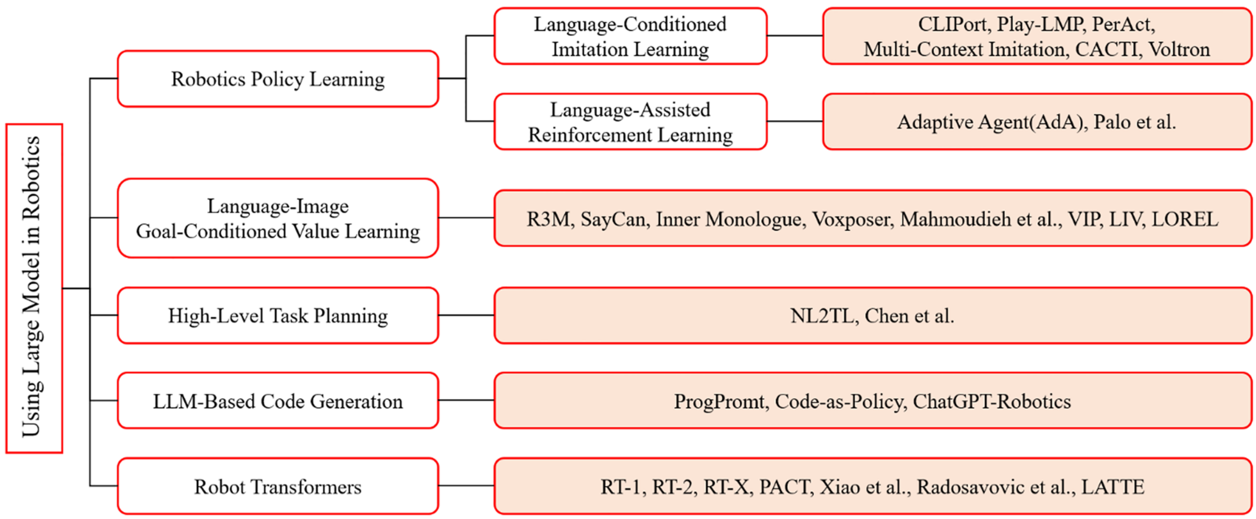

Figure 10 Application of large model technology in robotics [42]

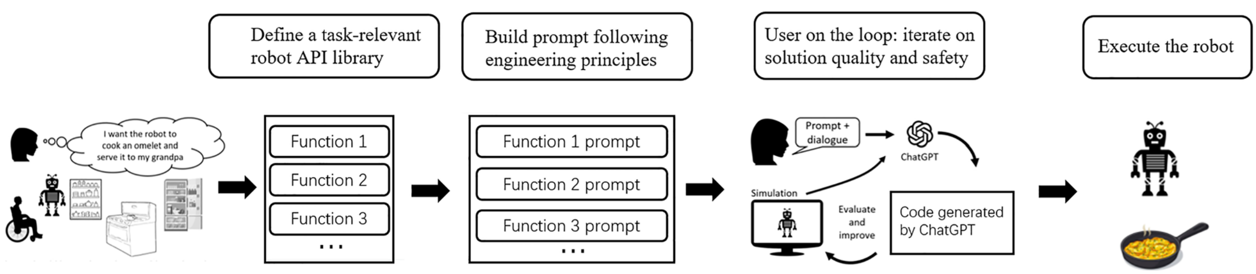

Figure 11 Steps of applying a large model to a robot for task execution [71]

integrating a large amount of data from robot execution tasks. Compared with traditional search and optimization based methods, this type of method can achieve end-to-end robot motion control, that is, through text or language instructions, the robot can complete the expected task. The development of these models provides new ideas and tools for trajectory generation strategies. With the great breakthroughs made by large model training technology in language processing, image processing and other fields, this technology has also been widely used in all aspects of the robotics field, such as task decomposition, code generation and trajectory generation, especially trajectory generation tasks. Through the application of large models, achieving end-to-end robot control has become a hot research topic for many scholars. The application of large model technology in robotics is illustrated in the figure below (Figure 10):

Research groups around the world are also starting to focus on training Foundation Models, such as large language models (e.g., GPT-3 and large vision models (e.g., ViT). In addition, there are basic models such as a multimodal language model and a visual generation model. When the large model training technology is applied to the research of robot motion control, the embodied intelligence model is subsequently developed. These models, through interaction with the environment, are capable of perception, mobility, autonomous decision-making, and learning, enabling machines to adapt and execute tasks within complex settings. The embodied intelligence model was proposed based on many research results. Building upon the advances in conversational AI achieved by OpenAI, researchers at Microsoft explored the feasibility of developing a robot that can comprehend human language input, interpret it and act upon user directives [71] (Figure 11). Another conceptual framework of the intelligent robot system RobotGPT has also been proposed, which enables robots to understand human language and automatically decompose, plan and execute tasks [72]. In some special scenarios, there are also applications of large language models in robot motion planning. For example, in scenarios where multiple objects are rearranged, large language models are used to obtain common sense knowledge and generate semantic robot actions to complete tasks [73]. Using a

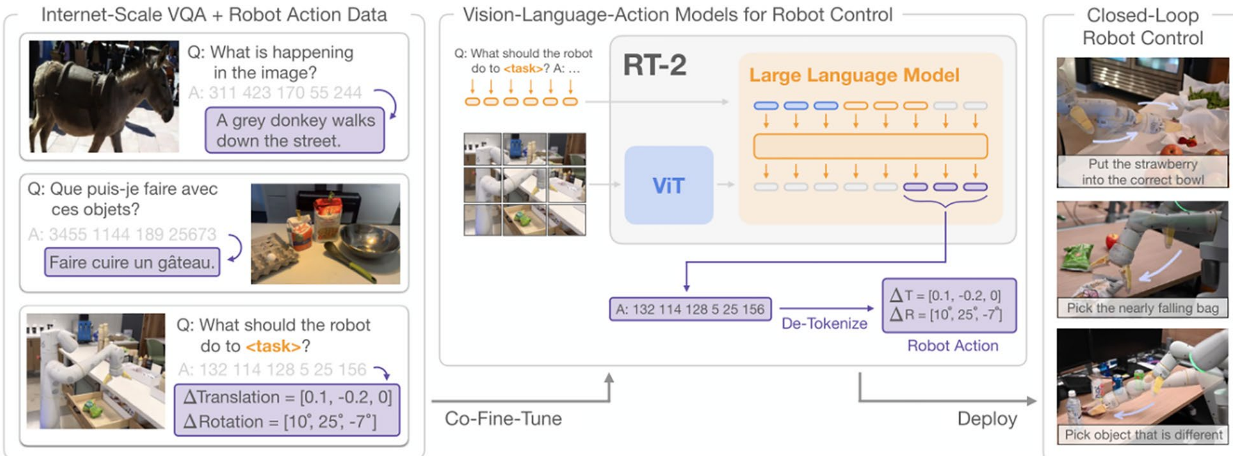

Figure 12 Schematic diagram of RT-2 model [76]

single model to solve motion planning for various robot tasks can better demonstrate the generalization ability of the model. For example, a framework called Text-2Motion combines natural language processing, large language models, and robot operation skills, enabling robots to solve complex sequential operation tasks based on natural language instructions [74]. With the addition of visual information, Researchers have developed the Vision-Language-Model (VLM), which integrates vision with large language models [75]. Additionally, the Vision-Language-Action (VLA) model translates image inputs into robotic actions through a language model [76]. As a result, research teams worldwide are actively pursuing the development of sophisticated embodied intelligence models to endow robots with autonomous perception, decision-making, and task execution capabilities in complex environments.

Nowadays, numerous research institutions have successfully pre-trained embodied intelligence models, equipping them with the capacity to receive task instructions and execute trajectory generation. According to the content of the pre-training data, embodied intelligence models can be roughly divided into trajectory generation for real robot operation tasks and trajectory generation for mobile robot navigation [77]. For contact tasks, a greater emphasis has been placed on the embodied intelligence model for real robot tasks, such as the model that combines the large language model and the vision model to establish a three-dimensional value map in space. This enables robots to generate trajectories to complete the target task guided by the generated map [78]. A notable example is the breakthrough RT-2 model developed by the Google team [76], which seamlessly combines the visual language model trained on Internet-scale data into the end-to-end robot motion control. This model uses both natural language description and number string to represent the robot action, match the numerical sequence provided by the model with the actual action of the robotic arm. Based on real-world training data, the RT-2 model annotates each robot trajectory with natural language instructions that describe the task performed. Through this approach, robots can generate corresponding actions in response to human commands, while also demonstrating generalization capabilities for novel commands not present in the training dataset. The robot can make autonomous planning in a new and unknown environment based on the human instructions (Figure 12). Building upon the RT-2 model architecture (visual encoding model and feature fusion decoding model), the Bytedance research team introduced the output of the feature fusion decoding model into the action prediction network, allowing the model to generate continuous action sequences through sufficient training [79].

Advancing the frontiers of embodied intelligence models is anticipated to catalyze a paradigm shift in robotic motion planning. Such innovation is likely to elevate the trajectory of robotics technology, fostering a more sophisticated tier of intelligent and automated capabilities. Consequently, this progression has the potential to exert a significant and enduring influence on the industrial automation sector. To provide an empirical foundation for this discourse, the tabulated data that follows offers a detailed overview of the current landscape of pre-trained embodied intelligence models.

It can be seen from Table 2 that when the embodied intelligence model solves the complete motion planning task, the amount of model data is relatively large [78–84]. In order to strengthen the performance of pre-trained large models in trajectory generation, many scholars have also tried to train and adjust part of the large model data with a small amount of data, a process called model fine-tuning. For example, the LoRA method simulates the effect of full parameter fine-tuning by introducing a low-rank matrix to achieve efficient parameter adjustment and reduce the computational complexity [85]. P-Tuning v2 method improves efficiency by adding learnable visual labels as prefixes and updating only the prefix parameters [86]. RLHF, which combines human feedback to train a reinforcement learning model to improve the quality of actions in line with human preferences [87]. For robot multi-contact interaction tasks, a small amount of real machine data can also be used to make the trajectory generated by the large model more smooth and stable. Using the appropriate model fine-tuning method can effectively reduce the resource consumption when using the embodied intelligence model.

In summary, the selection of an appropriate trajectory generation method is contingent upon a multitude of factors, including the intricacy of the task at hand, the environmental complexity, and the robotic system's degrees of freedom. The traditional search-based optimization methods and the nascent learning-based approaches each offer distinct advantages and can be tailored to the specific requirements of the robotic contact tasks. Furthermore, the conceptualization and ongoing development of embodied intelligence models present a more versatile and efficacious trajectory generation paradigm for robots engaged in contact tasks, enhancing the overall performance and adaptability of robotic systems in diverse operational contexts.

4 Simulation-to-reality Transfer

After generating a trajectory, it is crucial to develop an efficient approach for transferring simulated data to real-world scenarios. In general, both trajectory generation algorithms and trained models need to be validated in a simulation environment to verify their efficacy. The process of sim-to-real transfer involves bridging the gap between simulated outcomes and reality, mitigating discrepancies such as latency in trajectory generation, lag in action execution, and sensor noise in the environment [88]. This challenge can be addressed from two complementary perspectives: enhancing the simulation fidelity of the platform itself or devising methods to minimize errors during the sim-to-real transfer process. Recent advancements in simulation technology have led to the emergence of sophisticated platforms tailored for robot contact tasks, accompanied by numerous algorithms designed to facilitate seamless sim-to-real transfer [89].

4.1 Simulation Platform with Enriched Functions

With advancements in computing power and simulation technology, simulation environments have become increasingly capable of replicating the intricacies of the real world. This provides a richer platform for using robots to solve contact tasks. Many studies rely on these platforms to meticulously simulate the real physical environment, effectively mitigating task failures caused by discrepancies between the simulated and actual machine environments. For example, OpenAI's gym environment is widely used in the reinforcement learning of robots, allowing researchers to obtain substantial data within the simulation environment to achieve superior results [90]. With the help of the MuJoCo environment, Gu et al. use the DDPG algorithm to train the robot door opening task and obtain a 100% success rate after transferring the model into real scenes [91].

Another study realized the pen rotation operation of the manipulator in the simulation and real environment based on the Isaac sim platform [92]. In general, minimizing sim-to-real transfer errors on these simulation platforms largely depends on the potency of their physics engines and adaptability to real-world robot operating systems, such as the ROS (Robot Operating System).

Table 2 Embodied intelligence model parameters overview

Model	Architecture	Model scale	Pre-training tasks	Interaction frequency
RobotCat [79]	Decoder-only Transformer	1.18B	Motion Planning	10–20 Hz
PalM-E [80]	Decoder-only Transformer	562B	Task Decomposition and Motion Planning	5–6 Hz
ViNT [81]	EfficientNet + Decoder Transformer	0.5B	Visual Navigation	4 Hz
RT-2 [76]	PaLI-X	55B	Real Robot Operation Tasks	1–3 Hz
RT-2-X [82]	ViT + UL2 [83]	55B	Motion Planning	1–3 Hz
PACT [84]	Decoder-only Transformer	12M	Motion Planning	10 Hz
RoboFlamingo [78]	ViT + Transformer	80B	Motion Planning	*

* Indicates no found

A seamless integration can facilitate more researchers in conducting simulation experiments based on this platform. Several robot simulation platform parameters are shown below in Table 3, which can be used as a reference for selecting the simulation platform when performing simulation tests on contact tasks [92–96].

Currently, Gazebo is the most suitable simulation platform for the ROS system. Notwithstanding its increased complexity, it boasts an exceptionally comprehensive array of information and tutorials, rendering it highly convenient for users new to physics simulation. MuJoCo and OpenAI gym are better suited for physical simulation of traditional search optimization methods and emerging learning methods, respectively; however, their adaptability to ROS is relatively low, making them more suitable for users with prior experience in simulation platforms and robot hardware. MATLAB /Simulink, PyBullet and Isaac Sim feature user-friendly interfaces for testing the aforementioned path planning methods, among which the first two have low learning cost and are also suitable for people who are new to the simulation environment. Nevertheless, they demonstrate limited adaptability to ROS, necessitating additional work in sim-to-real transfer. Equipped with a commercial-grade physics engine and a machine learning platform maintained continuously by NVIDIA R&D, Isaac sim is better positioned for physics simulations using learning-based robotic path planning methods (Figure 13). Furthermore, the platform offers a wide array of models and scenarios. Presently, there is a notable increase in the number of studies focused on robot intelligent control that utilize this platform. In general, simulation platforms are becoming increasingly abundant and sophisticated, which significantly aids in reducing errors associated with sim-to-real transfer.

4.2 Simulation Migration Algorithm with Continuously Enhanced Environmental Adaptability and Elimination of Environmental Error

In addition to the employment of high-fidelity physical simulation platforms, the academic community is vigorously exploring strategies to mitigate existing discrepancies and address the sim-to-real transfer challenge.

Table 3 Comparison of simulation platforms

Simulation platforms	Main programming languages	Physics engine	ROS compatibility	Testing facilitation methods	Complexity level
Gazebo [92]	C++	ODE/Bullet/Simbody/DART	High	Search and Optimization Based methods	Medium
OpenAI gym [93]	Python	MuJoCo/Bullet	Low	Learning-Based methods	Medium
MuJoCo [94]	C/C++	MuJoCo	Low	Search and Optimization-Based methods	Medium
MATLAB/Simulink [94]	MATLAB	Simscape Multibody	Medium	All Methodologies	Low
PyBullet [95]	Python	Bullet	Medium	All Methodologies	Low
Isaac sim [96]	Python	PhyX	Medium	All Methodologies	High

Figure 13 Isaac Sim platform: providing a physical simulation environment for robots [97]

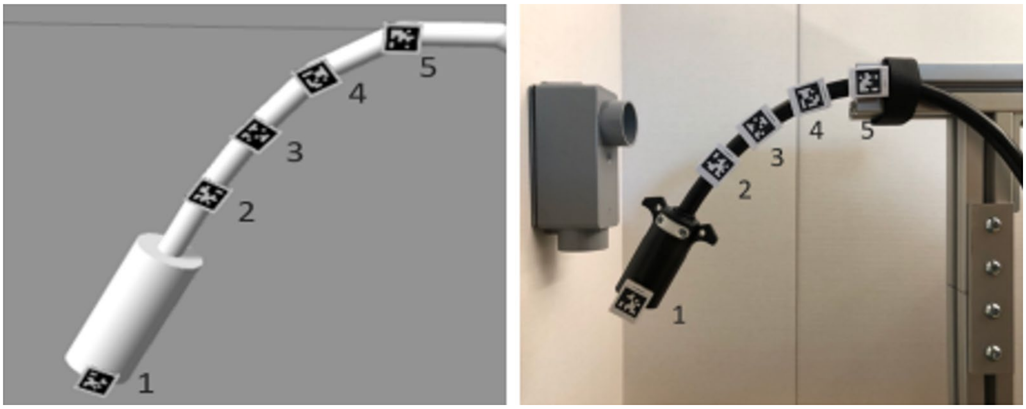

Figure 14 Real data acquisition via tag location synchronization to mitigate simulation errors [100]

Certain researchers have formulated differential models for the simulation transfer process, enabling the assessment of transferability from simulated to real-world scenarios, and have introduced methods to enhance this transferability, which have been substantiated through practical applications on two real robotic cases [98]. Other scholars have opted to utilize data generated by actual manipulators directly in the training phase when employing learning-based methods for robotic path planning. This approach effectively circumvents the sim-to-real transfer process, ensuring that the training is grounded in real-world data. For instance, as depicted in Figure 14, an array of markers is instrumental in ascertaining the precise spatial orientation of a soft robotic arm, thereby circumventing discrepancies arising from the transition between simulated and real-world environments [11, 99, 100]. In a similar vein, Peng et al. have integrated dynamic attributes into the simulation milieu to align it more closely with the sim-to-real transition process [101]. Collectively, these methodologies contribute significantly to enhancing the real-world adaptability of robotic systems.

In particular, the trajectory generation strategy based on reinforcement learning usually provides stochastic solutions, with heightened uncertainty during the machine-to-real-world transfer process, resulting in reduced performance. Therefore, many researchers have focused their efforts on investigating the simulation transfer process [102]. This body of work is primarily categorized into three distinct approaches: domain randomization methods, domain adaptive methods, and perturbation-based methods. Domain randomization involves extensively randomizing simulated environments to replicate real-world scenarios, thereby effectively capturing environmental nuances. However, this approach also exacerbates the demand for substantial data volumes and computational resources required for reinforcement learning [103]. In contrast, the domain adaptive methods use a single domain data to improve the performance of different target domains, so as to use the data obtained in the simulation environment to improve the policy effect in the real environment. This method is mainly applied to image classification and semantic segmentation tasks. This method has been successfully applied to guide the robot control tasks through the visual information obtained by the camera embedded in robots [104]. The concluding approach, which is the introduction of controlled perturbations, is a technique that involves the application of disturbances during the simulation training phase. This method is designed to enhance the model's resilience against environmental discrepancies that may arise when transitioning from simulated to real-world machine operations. By doing so, it aims to bolster the model's ability to generalize across a broader range of conditions, thereby improving its overall robustness and reliability in practical applications [105, 106]. These methodologies effectively mitigate the discrepancies between simulated and actual operational environments that are typically encountered when employing reinforcement learning-based trajectory generation techniques.

As the field of simulation technology continues to evolve and advance, coupled with the development of diverse sim-to-real transfer methodologies, the success rate of robots in executing contact tasks within real-world settings is anticipated to increase significantly. Concurrently, the ability of robots to adapt to complex environments will be substantially enhanced, facilitating a more robust and versatile performance in practical applications.

5 Summary and Outlook

The present paper provides a comprehensive review of the critical technologies that robots encounter when executing contact tasks within the realm of industrial automation, as illustrated in Figure 15.

Initially, the significance of environmental recognition is underscored, with a focus on the utilization of both independent modalities and multi-modal data fusion to enhance the robot's comprehension of its surroundings. As contact tasks grow in complexity, the predominant evolutionary trajectory involves the integration of an increasing array of modalities to bolster the precision of environmental recognition and analysis.

Subsequently, the paper delves into trajectory generation strategies, encompassing both conventional search and optimization-based techniques and the burgeoning learning-based approaches. Additionally, the incorporation of embodied intelligence models in trajectory generation is examined, highlighting the intelligent evolution of this field and its potential to offer a universal solution to trajectory generation challenges.

The discourse concludes with an exploration of sim-to-real transfer technology, addressing methodologies for the effective transposition of simulation-derived strategies to real-world applications. This is aimed at diminishing the divergence between simulated and actual environments. The ongoing enhancement of simulation platforms and the relentless pursuit of reducing simulation errors promise a progressive minimization of the gap between virtual and real-world scenarios. In the field of industrial automation, the future development of robot motion planning technology will focus on improving production efficiency, reducing costs and enhancing adaptability. On the one hand, it is necessary to further optimize the environment awareness algorithm and carry out research in the field of multimodal perception and dynamic environment adaptation to adapt to higher intensity production rhythm and more complex workpiece shape; On the other hand, more intelligent robot motion planning technology needs to be developed to give full play to the advantages of large language model and embodied intelligent model in Internet level experience. In addition, the safety and reliability of multi robot cooperative tasks and man-machine cooperative tasks are also important research directions to improve production efficiency. Future research endeavors may be directed towards the following directions:

(1) Advancement of environmental recognition technology: Leveraging the latest developments in sensor technology and data processing algorithms, the acquisition of more precise environmental data and the concurrent processing and analysis of a multiplicity of modalities can be achieved. This will fully exploit the analytical and comprehension strengths

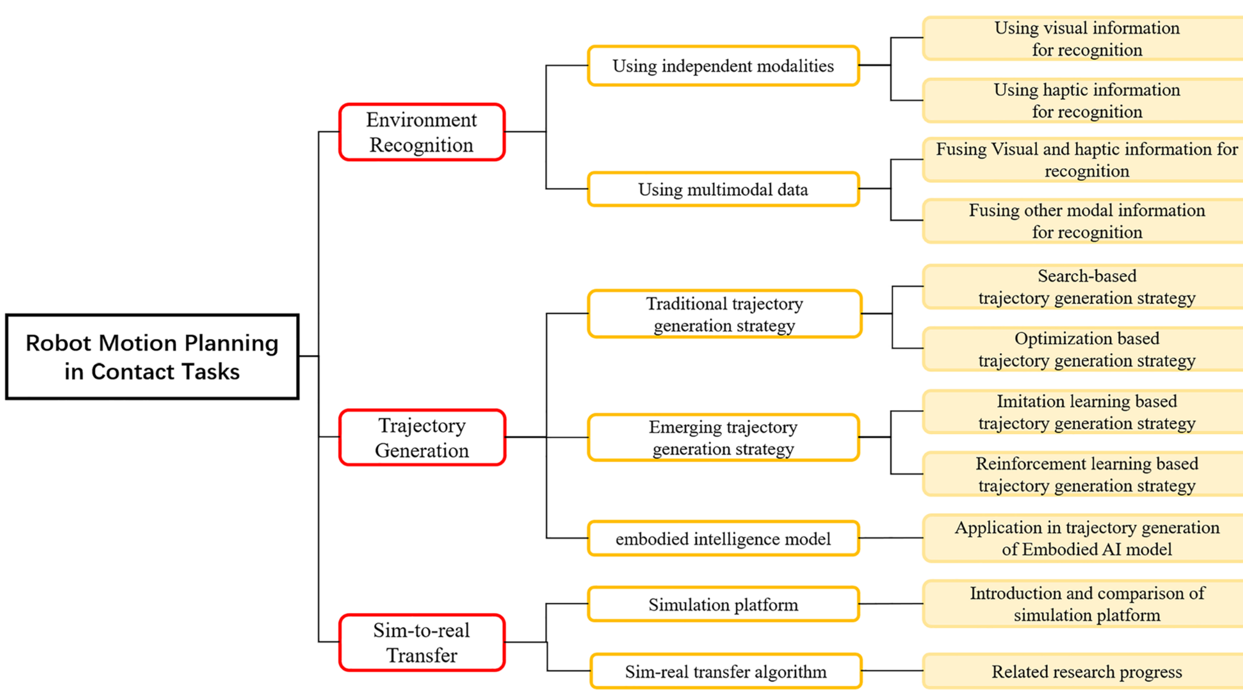

Figure 15 Overview of robot motion planning for contact tasks

of multimodal data fusion, rendering environmental recognition more accurate and timely, and further augmenting the robot's dynamic environmental adaptability.

(2) Innovation in trajectory generation strategies: By integrating cutting-edge artificial intelligence and machine learning advancements with traditional methods, the development of more intelligent and adaptive trajectory generation techniques can be pursued to address increasingly intricate tasks and environments. The integration of navigation technology and machine learning in autonomous driving provides a valuable reference point for this innovation.

(3) Refining and applying embodied intelligence models: By optimizing and fine-tuning embodied intelligence models, their performance in specific tasks can be significantly enhanced. This reduces computational resource demands and enables more efficient task execution by robots, thereby facilitating the industrial application of these models. For instance, a model trained for dual-arm cooperative control can be fine-tuned using a dataset specific to assembly tasks, which can markedly improve its performance.

(4) Advancement in sim-to-real transfer technology: The sophistication of simulation will be enhanced by exploring novel techniques and methodologies, such as photorealistic rendering and nonlinear dynamics simulation, to further bridge the gap with the real world. These technologies will greatly enhance the capabilities of simulation platforms, such as the Isaac Sim platform already supports parallel simulation of flexible structures, showcasing the potential for more realistic and efficient sim-to-real transfers.

(5) Interdisciplinary Integration: The future of robot motion planning lies in its convergence with fields like cognitive science and bionics. For example, based on the research of cognitive science, a robot motion planning algorithm which can simulate the human decision-making process has been developed, so that the robot can more flexibly adjust the strategy in the face of complex tasks. In terms of bionics, researchers have designed snake like and earthworm like robots, that can imitate the movement mode of organisms and show excellent movement ability in narrow space and complex environment. These interdisciplinary studies not only provide new ideas and methods for robot motion planning, but also open up broad prospects for future robot design and application. Future research will further explore the potential of these interdisciplinary fields and promote the continuous innovation and development of robot technology.

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Shibo Jin born in 2000, is currently a master candidate at *Beihang University, China*.

Kaichen Ke born in 1999, is currently a master candidate at *Beihang University, China*.

Boyang Gao born in 1984, received BS degree in computer science from *Xi'an Jiaotong University, China*, in 2006 and a MS degree in computer science from *Harbin Institute of Technology, China*, in 2009, and a PhD degree in computer science from *École Centrale de Lyon, France* in 2014. He is currently with Geometry Robotics Ltd. His research interests focus on robotics.

Li Fu born in 1986, is currently an assistant professor at the *Tribology and Systems Dynamics Laboratory (LTDS, UMR 5513 CNRS), Ecole Centrale de Lyon, France*. His research interests include machine learning for tribology, surface engineering, and data-driven modeling.

Xingrong Huang born in 1989, is currently an associate professor at *Beihang University, China*. She received her PhD degree in mechanics from *Ecole Centrale de Lyon, France*, in 2016. Her research interests include dynamics and control of robotics, aeronautics and aerospaces structures. Tel:+86-010-82316456;