

Review of machine learning in robotic grasping control in space application

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ABSTRACT

This article presents a comprehensive survey of the integration of machine learning techniques into robotic grasping, with a special emphasis on the challenges and advancements for space applications. The incorporation of artificial intelligence, particularly through deep learning, reinforcement learning, transfer learning, convolutional neural networks and recurrent neural networks, has significantly revolutionized robotic grasping. These advancements facilitate autonomous, efficient, and sophisticated manipulation in the challenging environment of outer space, transitioning from traditional mechanical grippers to sophisticated systems powered by advanced algorithms. This transition highlights the critical integration of sensory perception, grasp planning, and execution mechanisms, enhancing robots' capabilities to perceive, interact with, and manipulate objects with unprecedented precision and adaptability. The article meticulously outlines significant advancements achieved through the deployment of convolutional neural networks for visual information processing, RNNs for sequential decision-making, RL for autonomous strategy refinement, and transfer learning for leveraging pre-learned knowledge in novel tasks. These technologies address the unique challenges of space environments, such as varied textures, occlusions, microgravity conditions, and the sim-to-real gap, by enhancing sample efficiency, improving sim-to-real transfer capabilities, and integrating multimodal data for better object localization and pose estimation. Furthermore, the review explores the specific challenges faced in space robotic grasping, including handling varied textures and occlusions, adapting to unpredictable conditions, achieving real-time processing, and ensuring safety and reliability. It proposes future research directions focused on overcoming these hurdles, such as enhanced generalization through multimodal learning, robust sim-to-real transfer techniques, and the development of collaborative robotics and swarm intelligence. Critical to the development of ML models for robotic grasping are the roles of specialized datasets and simulation environments. Datasets like the Cornell Grasping Dataset and the Yale-CMU-Berkeley Object, along with simulation platforms such as Gazebo and PyBullet, provide essential resources for training, testing, and refining ML models. These tools enable researchers to simulate complex robotic systems and interactions within realistic environments, fostering rapid iterations on design and control strategies. In summary, this article offers in-depth insights into the progress, current challenges, and future prospects of machine learning techniques in robotic grasping for space exploration. It showcases significant strides made in the field and charts a path forward, emphasizing the need for innovative solutions to navigate the complexities of robotic manipulation in outer space. Through the strategic integration of advanced ML techniques, the development of adaptable and efficient robotic systems for space applications continues to advance, promising to unlock new possibilities in space exploration and beyond.

1. Introduction

An intelligent robot's capacity to perceive its environment and interact with it is paramount. Among these capabilities, the faculty of grasping stands out as both fundamental and profoundly impactful, poised to unleash significant advancements across various sectors of society [1,2]. Specifically, in the realm of space exploration, robotic systems equipped with sophisticated grasping abilities are instrumental.

Space robots, for instance, are pivotal in executing complex operations such as satellite servicing, debris removal, and the assembly of structures in the challenging environment of outer space. The pursuit of imbuing robots with perceptual intelligence aligns with the long-standing ambitions of both the computer vision and robotics fields, marking a critical step towards achieving autonomous extraterrestrial missions.

In the intricate domain of robotic grasping, particularly within the austere and unyielding confines of space, the synergy between the

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Abbreviations	
AI	Artificial Intelligence
CNNs	Convolutional Neural Networks
DDPG	Deep Deterministic Policy Gradient
Dex-Net	Dexterous Networks
DRL	Deep Reinforcement Learning
GANs	Generative Adversarial Networks
LSTM	Long Short-Term Memory
MBRL	Model-Based Reinforcement Learning
ML	Machine Learning
PBRL	Policy-Based Reinforcement Learning
RAM	Recurrent Attention Model
ReLU	Rectified Linear Unit
RL	Reinforcement Learning
RNNs	Recurrent Neural Networks
ROS	Robot Operating System
SR	Success Rate
VBRL	Value-Based Reinforcement Learning
YCB	Yale-CMU-Berkeley Object and Model Set

robotic arm, detector, and end effectors is paramount. These components form the backbone of any effective grasp detection system, each playing a pivotal role in the nuanced choreography of space operations. Robotic arms used in space, such as the Canadarm2 on the International Space Station or the robotic arms on Mars rovers like Perseverance, exemplify the critical balance between strength, precision, and versatility required in the vacuum of space. These arms must operate under the constraints of microgravity, execute complex maneuvers, and interact with a myriad of objects, from satellites to celestial terrain.

Detectors in space robotics often leverage cutting-edge technology to navigate the challenges of space. Sophisticated cameras, LiDAR systems, and other sensors are employed to provide detailed environmental data, enabling precise object detection, navigation, and interaction. For example, the use of stereo vision cameras on Mars rovers facilitates depth perception, crucial for accurate grasp planning and object manipulation. End effectors, tailored for the unique demands of space, range from simple grippers to complex tools capable of drilling, sample collection, and intricate repair tasks. These devices are designed to be as adaptive as possible, capable of handling the unpredictable and varied nature of spaceborne materials and surfaces. For instance, the specialized end effector on the Canadarm2 can grasp and maneuver objects of different sizes and shapes, illustrating the importance of versatility in space robotics.

An exemplar of such integrated system functionality is depicted in Fig. 1, showcasing a Kuka KR6 robot outfitted with an Intel RealSense Depth Camera D455 and a three-finger gripper. This configuration epitomizes the harmonization of sensory input, grasp planning, and execution mechanisms essential for robotic manipulation. While primarily utilized in terrestrial experiments, this setup mirrors the complexity and integration required for space exploration tasks, underscoring the potential for terrestrial technologies to inform and enhance extraterrestrial operations.

Robotic grasping systems comprising multiple interconnected sub-systems, each dedicated to facilitating precise and dependable grasping actions. In the context of space robotics, these sub-systems gain additional significance due to the unique challenges posed by the extraterrestrial environment. Notably, the robotic grasping system bifurcates into three primary components, as illustrated in Fig. 2 [4].

- **The Grasp Detection System:** A cornerstone for identifying viable grasping points on objects, this subsystem leverages advanced sensory inputs and computer vision techniques. Space missions often

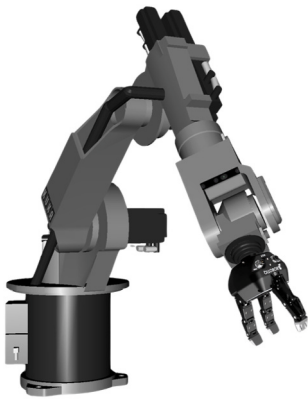


Fig. 1. Detailed view of the Kuka KR6 Robotic Arm [3] with advanced sensory and grasping capabilities. This image displays the Kuka KR6 robot, outfitted with an Intel RealSense Depth Camera D455 for enhanced perception and a versatile 3-finger gripper, demonstrating the integration of sophisticated sensory equipment and adaptable grasping mechanisms within a single robotic system. The setup serves as a terrestrial analogue for the complex systems deployed in space, offering insights into the future of robotic manipulation in extraterrestrial environments.

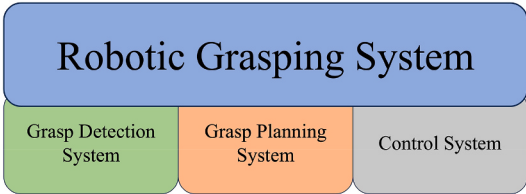


Fig. 2. Schematic representation of the robotic grasping system. This diagram illustrates the primary components of the robotic grasping system, showcasing the grasp detection system, the grasp planning system, and the control system as key subsystems. Together, they form a cohesive framework crucial for sophisticated manipulation tasks, particularly in the challenging environment of space.

utilize specialized detectors, such as LIDAR and radar, adapted for the vacuum and vast distances of space, to identify and analyze potential grasp points on satellites, debris, or other celestial objects.

- **The Grasp Planning System:** Following the identification of potential grasps, this subsystem undertakes the critical task of evaluating and selecting the most suitable grasp. It considers factors pivotal in space, such as the object's geometry, its orientation in microgravity, and the specific operational task—be it repair, assembly, or debris mitigation.
- **The Control System:** This subsystem is responsible for the actual execution of the grasp, orchestrating the movements and adjustments of the robotic arm and end effectors. Space robotic arms, such as the Canadarm2 on the International Space Station, exemplify the precision and reliability required for successful task execution in space. End effectors, ranging from standard grippers to more specialized tools designed for specific operations like satellite capture or module assembly, are tailored to operate under the unique conditions of space.

These subsystems, integral to the overall performance of robotic grasping systems, play indispensable roles in ensuring the success of robotic operations in space, highlighting the synergy between detection, planning, and execution in overcoming the challenges of extraterrestrial manipulation tasks.

The grasp detection system has significantly evolved with advancements in sensory technology, enabling a more nuanced interaction with the environment. Innovations in sensor devices, such as the Microsoft

Kinect and Intel RealSense, have revolutionized the way depth information of target objects is acquired, leading to the widespread adoption of RGB-D sensors in contemporary robotic grasping systems. Illustrated in Fig. 3 is a sophisticated Process Flow Diagram for an Automated pick-and-place operation, which seamlessly integrates a vision system equipped with an RGB-D camera. This process delineates the sequence from visual data acquisition of the target object, through pre-processing and analysis via deep neural networks for determining an optimal grasp configuration, to the meticulous mapping of the robotic manipulator's trajectory. This sequence encompasses everything from the initial approach for grasping to the precise placement of the object and the system's reversion to a standby state. The integration of visual perception with motion planning highlights the essential synergy between sensory input and mechanical action, emphasizing the need for advanced algorithms and techniques to enhance operational efficacy, particularly in complex environments like space where precision and adaptability are paramount.

Our discourse will primarily navigate through the intricacies of the grasp detection system, spotlighting its indispensable role within the robotic grasping paradigm and the avant-garde methodologies propelling its capabilities forward.

Venturing further, we dissect the cutting-edge domain of deep learning applications in robotic grasping, revealing that despite noteworthy advancements, the field confronts substantial challenges. The complexity inherent in real-world scenarios, coupled with the vast diversity of objects and the imperative for swift, real-time processing, presents significant obstacles. Anticipated future inquiries aim at bolstering adaptability and operational efficiency, especially critical in the face of dynamic and unforeseen environmental conditions. Through an exhaustive synthesis, this review not only showcases the achievements to date and the persistent challenges but also envisages prospective research avenues, charting a course for future exploration and innovation in the dynamic sphere of learning-based robotic grasping.

The article begins with an **Introduction** (Section 1), setting the stage

for the discussion by emphasizing the importance of robotic grasping in space exploration. Following this, **Background and Evolution of Robotic Grasping** (Section 2) delves into the historical progression from mechanical grippers to AI-driven systems. The core of the survey, **Fundamentals of Machine Learning in Robotic Grasping** (Section 3), dissects the roles of CNNs, RNNs, RL, and transfer learning in advancing grasping capabilities. To support these advancements, **Datasets and Simulation Environments** (Section 4) reviews essential datasets and simulation platforms that underpin ML model development and testing. **Challenges in Integrating Machine Learning with Robotic Grasping for Space Applications** (Section 5) outlines the hurdles faced in space environments, including data scarcity and the sim-to-real gap. Looking ahead, **Future Directions in Machine Learning for Robotic Grasping in Space Applications** (Section 6) proposes areas for research and development to overcome existing challenges and further enhance robotic autonomy and efficiency.

2. Background and evolution of robotic grasping

Robotic grasping represents a pivotal area of research within robotics, driven by its indispensable role across a myriad of applications from industrial automation and healthcare to the cutting-edge domain of space exploration [5–8]. The trajectory of robotic grasping's evolution mirrors the integration of increasingly advanced technologies, devised to navigate the complexities of manipulating objects in diverse and often unpredictable environments, with a particular emphasis on the unique challenges presented by space.

2.1. Early developments

The initial phase of robotic grasping research focused on developing mechanical grippers and simple control strategies [9]. These early systems were primarily designed for specific tasks with predictable and structured environments, such as assembly lines. The primary challenge

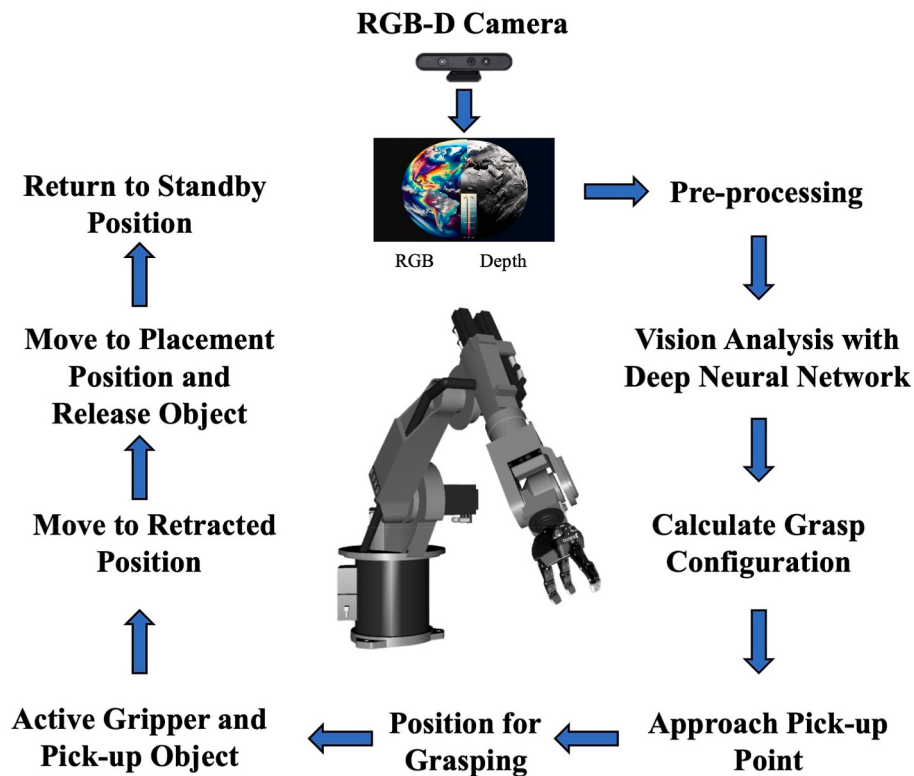


Fig. 3. Process flow diagram for a robotic manipulator in automated pick-and-place operations with vision system integration. This diagram showcases the integration of visual processing stages through an RGB-D camera, facilitating precise motion planning for the robotic arm during object manipulation.

was to create grippers that could apply sufficient force to hold objects without damaging them. Traditional approaches, largely reliant on pre-programmed strategies, have been limited in their adaptability and dexterity, particularly in unstructured or unfamiliar environments [10–12].

2.2. Recent progress

The advent of artificial intelligence (AI) and machine learning (ML) heralded a transformative era in robotic grasping [13–15]. Deep learning, in particular, has revolutionized the field, enabling robots to interpret complex sensory data, make informed decisions, and execute sophisticated grasping tasks with an unprecedented level of precision and adaptability [16–18]. This evolution is crucial for space robotics, where the ability to handle a variety of objects under microgravity conditions, without direct human intervention, is paramount [19,20].

2.3. Evolution of robotic grasping methods

The progression of robotic grasping methods is a testament to the remarkable advancements and paradigmatic shifts within the field, transitioning from the mechanical simplicity of early grippers to today's sophisticated, AI-enhanced systems. This evolution not only mirrors the broader advancements in robotics and artificial intelligence but also underscores the field's ongoing commitment to achieving higher levels of precision, adaptability, and autonomy in robotic manipulation. Fig. 4 provides a visual timeline of these key technological advancements and paradigm shifts, from the pre-2000s mechanical era to the AI-driven autonomy of the 2020s and beyond.

2.3.1. Pre-2000s: the mechanical era

Initially, robotic grasping relied heavily on mechanical principles, utilizing simple grippers coupled with fundamental control mechanisms. While these systems were adept at performing repetitive, predefined tasks, their capabilities were limited by a lack of flexibility and intelligence, rendering them unsuitable for complex or unpredictable environments.

2.3.2. Early 2000s: introduction of vision systems

The advent of vision systems in the early 2000s marked a pivotal enhancement in robotic grasping, equipping robots with the ability to “see.” This development significantly broadened their operational capabilities, facilitating a deeper interaction with and understanding of their surroundings. It laid the foundational stone for the integration of sensory information into the grasping process, heralding a new era of sophisticated control strategies.

2.3.3. Mid-2000s to early 2010s: sensor integration and initial machine learning applications

This period witnessed a shift towards the incorporation of an extensive array of sensors, including tactile and force sensors, into

robotic platforms. Simultaneously, the field saw the nascent application of machine learning techniques, enabling robots to make data-driven decisions. The introduction of feedback loops, where robotic actions could be adjusted based on sensory inputs, significantly bolstered their adaptability and responsiveness.

2.3.4. Late 2010s: deep learning revolution

Characterized by the deep learning revolution, the late 2010s fundamentally transformed the landscape of robotic grasping. Complex neural network architectures, such as Convolutional Neural Networks (CNNs) for image recognition and Recurrent Neural Networks (RNNs) for processing sequential data, endowed robots with unparalleled object recognition, decision-making, and precision in executing grasping tasks. This era underscored the potential of robots to learn and iteratively improve from their experiences, marking a significant leap in performance and capabilities.

2.3.5. 2020s and beyond: AI-driven autonomy and advanced manipulation

The ongoing era is distinguished by a concerted push towards AI-driven autonomy, characterized by the application of advanced machine learning models like reinforcement learning (RL) and Generative Adversarial Networks (GANs). These cutting-edge technologies are extending the frontiers of robotic grasping, facilitating operation in more complex and dynamic environments, notably in scenarios akin to space exploration. Robots are increasingly demonstrating human-like dexterity and decision-making skills, heralding a future where autonomous robotic manipulation across a broad spectrum of tasks becomes a reality, with minimal human oversight.

2.4. Summary and rationale for this review

This review aims to elucidate the significant strides made in robotic grasping, with an acute focus on its pivotal applications within the realm of space robotics. We dissect the evolution across two seminal phases: the integration of advanced sensors and feedback mechanisms, and the groundbreaking shift towards learning-based methods, particularly deep learning. These phases represent the core of modern robotic grasping's transformation, underscoring the transition from mechanical precision to cognitive adaptability. By exploring various neural network architectures, such as CNNs, RNNs, and RL models, we aim to furnish a detailed perspective on how these innovations have not only propelled robotic grasping forward but also how they stand to redefine the future of space exploration and operations [21–23].

2.4.1. Incorporation of vision and sensory systems

The advent of advanced vision and sensory systems represents a watershed moment in the evolution of robotic grasping, heralding a new era of sophistication and adaptability [24–29]. This transformative phase introduced the capability for robots to operate within complex, unstructured environments, an advancement of particular significance to the field of space robotics. In the vastness of space, where the luxury

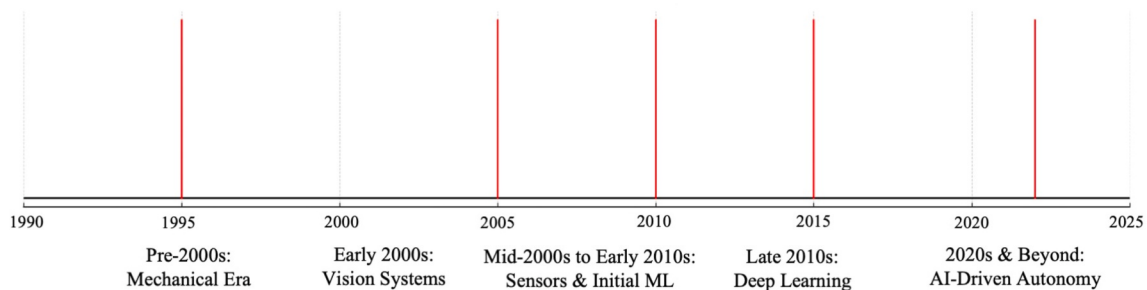


Fig. 4. Evolution of robotic grasping methods from the pre-2000s mechanical era to the 2020s and beyond. This timeline highlights key technological advancements and paradigm shifts in robotic grasping, illustrating the transition from simple mechanical grippers to sophisticated AI-driven systems.

of structured environments and human intervention is absent, the ability for robotic systems to “see” and “feel” becomes indispensable.

Equipping robots with a diverse array of sensors, including but not limited to tactile and vision systems, has empowered them to collect vital real-time information about their surroundings and the objects within. This sensory data enables robotic systems to dynamically adjust their grasping strategy, modifying grip strength and positioning to optimize the interaction with objects of varying shapes, sizes, and textures [30,31]. Such adaptability is crucial in space, where the unpredictable nature of objects—from satellite components to potential Martian samples—demands a high degree of precision and flexibility.

The integration of these sensory inputs with advanced control algorithms has further elevated the capabilities of robotic grippers, allowing for the processing of complex sensor data and its conversion into precise, actionable instructions [32,33]. This period also marked the beginning of the convergence between machine learning and robotic grasping, laying the foundational stones for the application of more sophisticated AI techniques that would later revolutionize the field. The effectiveness and efficiency of these sensor-integrated systems in space robotics can be quantified through metrics such as the success rate (SR), defined as:

$$SR = \frac{N_{\text{successful}}}{N_{\text{total}}} \quad (1)$$

here, $N_{\text{successful}}$ denotes the number of successful grasps, while N_{total} signifies the total number of grasping attempts, offering a quantifiable measure of a system's performance in the challenging conditions of space.

2.4.2. Incorporation of learning-based methods

The integration of learning-based methodologies, particularly deep learning, marks a pivotal advancement in the domain of robotic grasping, heralding an era of unparalleled dynamism and adaptability [34,35]. This shift is of paramount importance in the context of space robotics, where the capacity for autonomous learning and adaptation is critical. Space missions, characterized by object manipulation, repair, or assembly in extraterrestrial environments, demand robotic systems that can autonomously improve and adapt to the unpredictable nature of space.

Deep learning, an evolved subset of machine learning, employs sophisticated neural network architectures, such as CNNs for intricate image processing tasks, and RNNs for managing sequential data. These advanced computational models enable robotic systems to process extensive sensory information, facilitating informed decision-making and the execution of complex grasping operations with remarkable precision. The advent of deep learning has significantly narrowed the gap between robotic capabilities and human dexterity, empowering robots with a quasi-intuitive understanding of their operational environment.

The profound impact of deep learning on the field extends robots' abilities beyond mere programmed responses, allowing for an iterative learning process that mimics human cognitive processes in decision making and problem-solving. This capability is particularly crucial in the unstructured and dynamic environment of space, where pre-programmed instructions are insufficient to handle the myriad of unexpected challenges. Through deep learning, robots can now recognize patterns, adapt to new scenarios, and refine their grasping techniques based on a continuous influx of sensory data, thereby enhancing their operational efficacy in space exploration and utilization.

The essence of deep learning's contribution to robotic grasping lies not only in its ability to process and analyze vast datasets but also in its capacity to learn from each interaction, continuously improving its accuracy and efficiency in object manipulation. This evolutionary leap in robotic intelligence opens new horizons for space robotics, promising significant advances in our ability to explore, understand, and operate in outer space.

2.5. Past coverage

Table 1 offers a detailed overview of seminal survey and review articles, tracing the progressive evolution through key methodologies, transformative contributions, and the integration of machine learning innovations. This summary adeptly encapsulates the diverse approaches and breakthroughs that have significantly influenced the contemporary landscape of robotic grasping.

3. Fundamentals of machine learning in robotic grasping

The incorporation of machine learning into robotic grasping has marked a significant milestone in the field's evolution, particularly underlining its vital role in space exploration. The autonomous handling of unknown objects in space necessitates accurate object pose estimation—a task fraught with challenges due to objects' varied textures, potential occlusions, and the intrinsic unpredictability of the outer space environment. Initially, the reliance on 3D models for partial registration provided essential insights but fell short in addressing the full spectrum of complexities associated with objects in space.

The advent of deep learning has dramatically amplified the ability of robotic systems to ascertain highly accurate 6D object poses from simple RGB images, revolutionizing space robotics [1]. This progress allows for enhanced interactions with objects for critical tasks such as satellite repair, the assembly of space structures, or the collection of scientific samples. Achieving a precise understanding of an object's orientation and position is indispensable in the microgravity conditions of space, where precision and dependability are paramount.

As focus shifts towards grasp estimation, the methodologies adapt to meet the specific demands of space missions. The array of strategies includes evaluating potential contact points for 2D planar grasps and deliberating whether to utilize partial point clouds or a complete object model for more complex 6DoF grasp estimations. Space, with its scarcity of familiar objects and the likelihood of encountering novel entities on each mission, necessitates methods that do not rely on pre-existing models. These include techniques for assessing grasp quality or leveraging existing grasp strategies on newly discovered objects.

Machine learning advancements have notably widened the range of objects that robotic systems can manage, simultaneously enhancing the robustness and adaptability of grasping techniques—qualities that are especially vital for space missions. This progression promises to significantly augment the capabilities of robots in space, empowering them to undertake a broader spectrum of tasks with enhanced autonomy.

3.1. Object localization

Object localization assumes a critical role in the expansive and unpredictable domain of space. Powered by deep learning, particularly through the use of CNNs, this task focuses on the accurate identification and positioning of objects against the backdrop of space. Such capabilities are essential for identifying satellite components during servicing missions or for tracking space debris to prevent collisions, with the precision and dependability of localization directly influencing the success of subsequent robotic missions.

3.2. Object pose estimation

Accurate object pose estimation is crucial for the successful execution of complex robotic tasks in space, such as docking, assembly, and repairs. The application of deep learning, through CNNs and occasionally RNNs, to infer the 3D pose of objects from visual data, represents a significant advancement. This methodology provides space robots with the ability to precisely understand the spatial orientation and positioning of objects, a critical requirement for navigating the complexities of space.

Table 1

Comprehensive overview of survey and review articles on robotic grasping: from foundational techniques to cutting-edge innovations. This table encapsulates the critical contributions and methodological evolutions within the field, charting the journey from initial mechanical concepts to the integration of advanced machine learning algorithms.

Study	Year	Main Focus	Key Findings/ Contributions	Methodologies Covered
Chen et al. [36]	2022	Space intelligent grasping robots	Reviews technologies for configuration design, dynamic modeling, and control algorithm in space robotics	AI-based problem-solving technologies
Papadopoulos et al. [37]	2021	Manipulation and capture in space	Addresses dynamics of SMS, contact dynamics, and feedback control methods	Sensing pose, motion planning, feedback control
Flores-Abad et al. [38]	2014	Space robotics for on-orbit servicing	Literature review on kinematics, dynamics, control, and verification of space robotic systems	Kinematics, dynamics, control strategies
Ellery [39]	2019	Robotics aspects of active debris removal	Reviews kinematics, dynamics, and control of manipulators for debris removal	Spacecraft attitude stabilization, computational issues
Li et al. [6]	2019	Machine learning in robotic grasping	Summarizes research progress and discusses unsolved problems in robotic grasping	Deep learning, reinforcement learning
Dong and Zhang [7]	2023	Robotic grasp detection	Literature review focusing on analytic and data-driven methods for grasp detection	Data-driven methods for known and unknown objects
Du et al. [1].	2019	Vision-based robotic grasping	Comprehensive survey on key tasks in vision-based robotic grasping	Object localization, pose estimation, grasp estimation
Tian et al. [40]	2023	Robotic visual grasping detection for unknown objects	Reviews object-oriented and scene-oriented aspects of DRVGD	Object classification, scene exploration
Xie et al. [41]	2023	Learning-based robotic grasping	Reviews developments in learning-based techniques for flexible object grasping	3D object segmentation, tactile sensors
Yamanobe et al. [42]	2017	Affordance in robotic manipulation	Discusses affordance applications in grasping and manipulation	Learning from human, simulation, real-world execution
Wang et al. [43]	2020	Robotic grasping of objects with uncertain information	Reviews work on feature sensing and robotic grasping with uncertain information	Learning-based approaches for uncertain objects
Duan et al. [44]	2021	Dexterous grasping using point cloud	Reviews methods for dexterous grasping from generation-	Point cloud, deep learning

Table 1 (continued)

Study	Year	Main Focus	Key Findings/ Contributions	Methodologies Covered
		and deep learning	evaluation framework perspective	

3.3. Grasp estimation

Advancements in deep learning extend beyond Earth's confines, enhancing grasp estimation for space missions. This process not only involves determining the most effective grasp points but also adapting to the unique challenges presented in space. Reinforcement learning emerges as a promising approach, enabling robots to iteratively improve their grasping strategies, thereby boosting their autonomy and operational efficiency in space endeavors.

3.4. CNNs in robotic grasping

CNNs have become indispensable in processing visual information for robotic grasping, particularly in the domain of space exploration where identifying and interacting with objects of diverse characteristics is paramount. The convolution operation, foundational to CNNs, is mathematically represented as:

$$G(x, y) = \sum_{i=-a}^a \sum_{j=-b}^b F(i, j) \cdot H(x - i, y - j) \quad (2)$$

where $G(x, y)$ denotes the convolution's output at pixel location (x, y) , derived from the input image $F(i, j)$ through the transformative lens of the kernel $H(x - i, y - j)$. This operation iterates across the image, with the kernel accentuating vital features such as edges and textures, thereby transforming the input into a feature-rich map.

The introduction of non-linearity through the Rectified Linear Unit (ReLU) function, $f(x) = \max(0, x)$, is crucial for modeling complex data patterns. ReLU enhances network performance by facilitating faster training without compromising the ability to represent intricate relationships within the data.

Pooling operations, particularly max pooling represented as $P(x, y) = \max_{(i, j) \in W} F(i, j)$, further distill the feature map by downsizing its spatial dimensions while retaining salient features. This step is instrumental in reducing computational demand and bolstering feature detection's resilience to positional variations.

These CNN elements—convolution, ReLU, and pooling—create a robust framework for visual data interpretation, vital for space robotics' unique needs. Accurate object identification and feature extraction are essential for successful object manipulation in space, where conditions demand unprecedented precision.

Fig. 5 exhibits a CNN architecture tailored for robotic grasping, integrating residual connections that facilitate the forward propagation of contextual data and features. This architecture underscores the progressive complexity in feature extraction, from initial layers capturing basic aspects to deeper layers discerning intricate details. The architecture culminates in a softmax layer, categorizing the input into one of several predefined classes, epitomizing the CNN's ability to classify images effectively.

This specialized CNN structure, designed with residual connections, optimizes the transition from raw visual input to actionable grasping decisions. It exemplifies how machine learning, particularly deep learning, is advancing the capabilities of space robots, enabling them to recognize and interact with objects in space with heightened accuracy and efficiency.

Table 2 provides a meticulously curated overview of seminal research leveraging CNNs specifically for object localization. These highlighted works reveal the extensive applicability of CNNs, ranging from bolstering real-time detection and localization precision to the

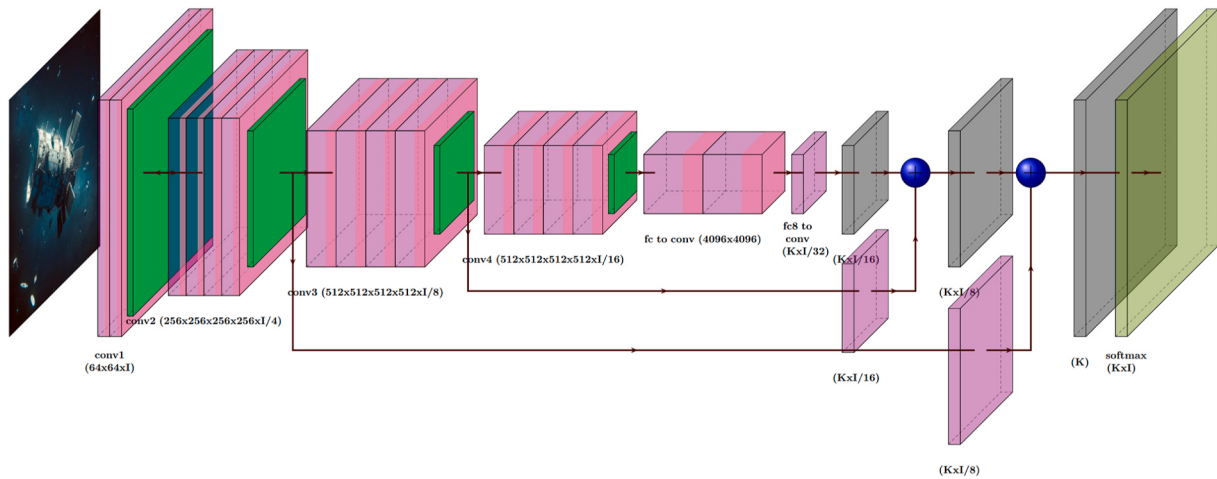


Fig. 5. Detailed architecture of a CNN with residual connections tailored for robotic grasping in space applications. This architecture illustrates the layer-wise progression for deep feature extraction and classification, underpinning the nuanced visual processing necessary for accurate object recognition and manipulation by space robots.

Table 2

Utilization of CNNs for object localization in robotic grasping. This table highlights key research efforts employing convolutional neural networks for the precise localization of objects, a fundamental step towards effective robotic grasping.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Rais et al. [45]	2023	Cascade of CNNs for Object Positioning	Introduced a novel approach using a cascade of CNNs (YOLOv5 and EfficientNet) for object detection and rotation angle classification, achieving high precision and recall rates.	YOLOv5, EfficientNet, Image Processing Techniques
Farag et al. [46]	2019	Real-Time Grasping and Localization	Demonstrated 100 % precision in object detection and real-time grasping using the KSSnet model, a CNN developed on the Alexnet framework, for robotic grasp-and-place operations.	Deep Convolutional Neural Network (KSSnet), Edge Detection, Camera Calibration Techniques
Jia et al. [47]	2018	Unified Deep CNN for Grasping	Proposed a network framework that simultaneously performs classification, localization, and grasp detection, showing effective real-time grasping on a robotic manipulator.	Deep Convolutional Neural Network with Multi-task Loss, Region Proposal Techniques
Trottier et al. [48]	2017	Grasp Localization with Residual Networks	Utilized residual networks for grasp localization, addressing the challenge of spatial correlation removal by modifications in architecture, achieving state-of-the-art performance.	Convolutional Residual Network, On-line Data Augmentation

integration of multifaceted deep learning frameworks that concurrently undertake object recognition and localization tasks. The deployed methodologies showcase the strategic adaptation of CNN architectures and techniques, meticulously crafted to address the nuanced requirements of robotic grasping endeavors. By harnessing a suite of deep learning innovations, including cutting-edge network designs, these investigations have realized unprecedented levels of accuracy and efficiency in the realm of object localization. A prominent theme, as illustrated by Rais et al. [45], and Farag et al. [46], is the integration of advanced CNN architectures such as YOLOv5, EfficientNet, and custom models like KSSnet. These approaches emphasize the importance of utilizing sophisticated CNN structures to achieve high precision and recall rates in object detection and real-time grasping. The cascade of CNNs and the development of models based on foundational frameworks like Alexnet underline the relentless pursuit of accuracy and speed in object localization tasks. Another critical advancement is the move towards multi-tasking and unified frameworks for simultaneous classification, localization, and grasp detection, as proposed by Jia et al. [47]. This approach underscores the versatility of CNNs in handling multiple aspects of robotic grasping within a single, cohesive framework, showcasing an effective method to streamline the processing pipeline and enhance real-time grasping capabilities on robotic manipulators. The utilization of residual networks for grasp localization, highlighted by Trottier et al. [48], represents a leap in addressing the intrinsic challenge of spatial correlation in CNNs. By introducing architectural modifications and leveraging on-line data augmentation techniques, these studies pave the way for achieving state-of-the-art performance in grasp localization tasks, illustrating the crucial role of innovative CNN architectures in overcoming historical obstacles.

In the quest to enhance robotic capabilities for space exploration, significant attention has been directed towards refining object pose estimation using CNNs. Precise estimation of an object's pose is crucial for executing autonomous manipulations in the complex and variable environment of space. Table 3 summarizes recent advancements in CNN-based object pose estimation, shedding light on methodologies that contribute to the precision, efficiency, and adaptability of robotic systems in space. These studies not only illustrate the versatility and power of CNNs in tackling diverse geometric and textural challenges presented by objects but also underscore the potential for these techniques to revolutionize robotic grasping and manipulation. The work by Zheng et al. [49] exemplifies the drive toward creating CNN models capable of accurately estimating grasping poses across diverse objects and environmental conditions. This emphasis on adaptability and precision, facilitated by models like KSSnet, showcases the potential of CNNs in

Table 3

Advancements in CNN-based object pose estimation for robotic grasping: implications for space robotics. This table delves into key research efforts utilizing convolutional neural networks to refine object pose estimation, a critical step towards enabling precise and autonomous robotic manipulations.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Zheng et al. [49]	2023	Grasping Pose Estimation with CNNs	Developed a CNN model (KSSnet) that outputs grasping success rates, approach angles, and gripper opening widths. Demonstrated high adaptability and precision in grasping diverse objects, including in cluttered scenes and under varied lighting conditions.	KSSnet based on Alexnet, Transfer Learning, Edge Detection
Amini et al. [50]	2022	Transformer-Based Multi-object 6D Pose Estimation	Developed YOLOPose, a Transformer-based method using keypoint regression for 6D pose estimation, showcasing real-time application suitability and comparable state-of-the-art results.	Transformers, Keypoint Regression, Orientation Estimation Module
Wang et al. [51]	2022	6D Pose Estimation for Autonomous Manipulation	Proposed a method combining semantic segmentation CNNs with fast global registration for 6-DoF pose estimation, significantly improving autonomous grasping accuracy and speed.	Fully Convolutional Neural Network, Fast Global Registration
Peng et al. [52]	2022	6D Pose Estimation in Industrial Settings	Introduced a hybrid pose estimation method combining CNNs with template-based estimation to handle occlusions and texture-less objects in cluttered industrial scenes.	Template-based Estimation, CNN, Hybrid Methodology
Papaioannidis et al. [55]	2019	Multi-Objective Quaternion Learning for 3D Pose	Proposed a CNN framework employing a quaternion-based multi-objective loss function for direct 3D object pose estimation from RGB images,	Quaternion-based Learning, Manifold Learning, Regression

Table 3 (continued)

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Tshilombo et al. [53]	2018	Dataset Generation for Pose Estimation	showcasing superior accuracy and generalizability. Introduced a method for generating large training datasets for CNNs from a set of images using structure from motion and domain randomization, facilitating object pose estimation from RGB images.	Structure from Motion, Domain Randomization, ConvNet Training
Josifovski et al. [54]	2018	CNNs Trained with Synthetic Data for Pose Estimation	Combined the robustness of CNNs with instance-based 3D pose estimation, training models with synthetic data for high precision on real-world images, suitable for robotic grasping tasks.	Synthetic Training Data, Instance-based 3D Pose Estimation

navigating the complexity of space robotics applications, where varied lighting and cluttered scenes are prevalent. Amini et al. [50] introduce YOLOPose, leveraging Transformer technology for 6D pose estimation. This advancement points to the growing importance of integrating cutting-edge neural network architectures with traditional CNN approaches to enhance real-time application suitability and achieve state-of-the-art results, crucial for the dynamic environments encountered in space. The studies by Wang et al. [51] and Peng et al. [52] highlight innovative methods that combine CNNs with techniques like semantic segmentation, fast global registration, and template-based estimation. These hybrid approaches improve accuracy and speed in autonomous grasping and offer solutions to challenges like occlusions and texture-less object recognition in cluttered or industrial settings—factors that are paramount in the unpredictable terrain of space robotics. The generation and utilization of large, synthetic datasets for CNN training, as discussed by Tshilombo et al. [53] and Josifovski et al. [54], underscore the significance of domain randomization and synthetic data in overcoming the limitations of real-world data availability. This approach is particularly relevant in space robotics, where the collection of extensive real-world datasets is impractical or impossible, thus facilitating more efficient model training and generalization.

Table 4 compiles seminal works that leverage CNNs specifically for the intricate tasks of grasp estimation and detection. These selected studies represent a broad spectrum of strategies, each uniquely designed to navigate the inherent challenges of robotic grasping, including the variability of objects, the complexity of environments, and the imperative for real-time operation. At the heart of these advancements is the strategic use of CNNs, celebrated for their exceptional capability in extracting features and analyzing images, which have been adeptly tuned to enhance the accuracy and dependability of grasp detection mechanisms. From innovative generative models aimed at refining the accuracy of grasp point identification to streamlined networks optimized for swift implementation in environments with limited resources, the methodologies detailed in this table illustrate the ongoing evolution

Table 4
Advancements in CNN applications for grasp estimation and detection: elevating robotic precision and efficiency. This table delineates the significant strides made through the application of CNNs in grasp estimation and detection, showcasing how these methodologies refine robotic interactions with objects by enhancing precision and adaptability.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Li et al. [56]	2022	Robot Grasp Detection	Introduced a generative CNN model for accurate robot grasp detection in real-world scenes, utilizing Gaussian-based guidance and deformable convolution for enhanced object shape feature extraction.	Generative CNN, Gaussian-based Guidance, Deformable Convolution
Cao, BY et al. [57]	2022	Grasp Detection for Fragile Fruits	Designed four CNN models for the detection of grasping positions on fruits, utilizing data augmentation and transfer learning for enhanced model accuracy and generalization.	Xception, MobileNetV3, DenseNet, Transfer Learning
Zhang and Wu [61]	2021	Single Target Grasp Detection	Proposed a CNN-based network for high-accuracy, end-to-end grasp detection, emphasizing transfer learning and dataset preprocessing for model generalization.	End-to-End CNN, Transfer Learning, Dataset Preprocessing
Jiang et al. [58]	2020	Light-weight CNN Model for Grasp Detection	Proposed a light-weight CNN model, SqueezeNet-RCM, for real-time grasp detection, combining high accuracy with efficiency suitable for FPGA deployment.	SqueezeNet-RCM, Real-time Detection
Chen, L et al. [59]	2019	Multi-grasp Detection for RGBD Images	Developed a novel grasp detection model that evaluates grasp candidates through a grasp path, enhancing accuracy by considering the distribution of possible ground truths.	Convolutional Multi-Grasp Detection, Grasp Path Evaluation
Zhou et al. [60]	2018	Real-Time Grasp Detection	Presented a fully convolutional network with an oriented anchor box mechanism for predicting multiple grasping poses, achieving state-of-the-art accuracy on the Cornell Grasp Dataset.	Fully Convolutional Network, Oriented Anchor Box
Jia et al. [47]	2018	Unified CNN for Grasp Detection	Introduced a unified deep CNN framework capable of simultaneous object recognition, localization, and grasp detection, optimizing the	Unified Deep CNN, Multi-task Loss

Table 4 (continued)				
Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Kumra and Kanan [4]	2017	Deep CNN for Robotic Grasp Detection	process through a multi-task loss function. Demonstrated a novel robotic grasp detection system using a deep CNN, setting a new benchmark for accuracy in real-time grasp detection applications.	Deep Convolutional Neural Networks, Real-time Processing

of techniques in grasp detection. Furthermore, these studies spotlight the adoption of sophisticated CNN architectures, such as deformable convolutions and oriented anchor boxes. These developments empower robotic systems to accurately recognize and adjust to the diverse and complex nature of objects and the various scenarios they may encounter during grasping tasks. A notable trend, as seen in the works of Li et al. [56] and Kumra and Kanan [4], revolves around the innovation in CNN architectures, such as the introduction of generative models and deep convolutional networks. These advancements not only elevate the accuracy of grasp detection in real-world scenarios but also enhance the feasibility of real-time processing for robotic applications. The utilization of features like Gaussian-based guidance and deformable convolution underlines the shift towards models that can dynamically adapt to the complex geometries of objects. The development of CNN models tailored for specific challenges, such as the grasp detection for fragile fruits by Cao et al. [57], highlights the specialization trend within this domain. This approach leverages data augmentation and transfer learning to create models that not only perform with high accuracy but also exhibit an impressive capacity for generalization across various contexts. Jiang et al. [58] introduce a lightweight model, SqueezeNet-RCM, designed for efficient real-time grasp detection. This emphasis on creating models that balance accuracy with computational efficiency reflects the growing consideration for models' deployability in real-world applications, particularly on hardware with limited processing capabilities like FPGAs. Chen et al. [59] and Zhou et al. [60] explore multi-grasp detection, employing novel mechanisms such as oriented anchor boxes and grasp path evaluations. These methodologies enable the prediction of multiple grasping poses and the evaluation of grasp candidates, respectively, showcasing a nuanced approach to understanding the plethora of grasping options available for a given object. This evolution points to a more sophisticated analysis of potential grasps, enhancing the adaptability of robotic systems to a wider range of objects and scenarios.

3.5. RNNs in robotic grasping

RNNs, notably Long Short-Term Memory (LSTM) networks, distinguish themselves in the realm of robotic grasping through their adeptness in managing sequential decision-making tasks. Unlike CNNs and other feedforward architectures, RNNs are inherently designed to process sequential data, a capability that proves invaluable in applications where understanding temporal dynamics is paramount. This trait is particularly beneficial in the realm of robotic grasping, where the anticipation and coordination of movements based on a sequence of sensory inputs are critical.

RNNs excel in the analysis of time-series sensor data, enabling the prediction of an object's evolving state and facilitating the formulation of dynamic grasping strategies. The foundational structure of RNNs revolves around the hidden state (h_t), which acts as a repository of accumulated historical information, thus permitting the network to render decisions that are contextually informed by past events:

$$h_t = \sigma(W_{ih} \cdot X_t + W_{hh} \cdot h_{t-1} + b_h) \quad (3)$$

where h_t is the hidden state at time t , σ denotes the activation function, W_{ih} and W_{hh} represent the input-to-hidden and hidden-to-hidden weights respectively, X_t is the input at time t , and b_h is the hidden bias. This recursive framework enables RNNs to generate predictions on future states, a capability crucial for the dynamic evaluation of grasping actions.

$$Y_t = \sigma(W_{ho} \cdot h_t + b_o) \quad (4)$$

where Y_t is the output at time t , W_{ho} are the weights from the hidden layer to the output layer, and b_o is the output bias.

In robotic grasping, RNNs, particularly LSTMs, have demonstrated considerable utility across various applications, from the enhancement of 3D object recognition to the execution of adaptive manipulation strategies. Notably, LSTMs have been successfully applied for real-time slip detection, an essential component for securing a reliable grip on objects [62].

Fig. 6 illustrates an LSTM cell, integral to LSTM networks designed to learn and maintain long-term dependencies. The LSTM cell processes inputs at each time step (x_t) in conjunction with the preceding hidden (h_{t-1}) and cell (c_{t-1}) states. It employs gating mechanisms—namely, the forget gate (f_t), input gate (i_t), and output gate (o_t)—to selectively regulate the information flow. These gates decide which information to retain, discard, or output, thereby enabling the LSTM to effectively address the vanishing gradient dilemma and excel in tasks requiring comprehension of long-term sequential dependencies.

RNNs play a pivotal role in robotic grasping, especially in estimating stable poses for object manipulation within unstructured environments. By analyzing sensor data sequences, RNNs facilitate the examination and selection of optimal grasping strategies, enhancing robotic proficiency in executing complex manipulative tasks [63].

The sparse but impactful works leveraging RNNs for object localization highlight the adaptive potential of these networks in enhancing robotic perception and interaction with their environment. Despite the dominance of CNNs in spatial data processing tasks like object detection and pose estimation, RNNs introduce a unique capability to incorporate temporal dynamics and sequential dependencies in the robotic perception process. This attribute is particularly advantageous in scenarios

where objects' positions change over time or when the observation sequence significantly influences the localization accuracy.

However, it is worth noting that the scarcity of literature explicitly focusing on RNN applications for object localization and pose estimation underscores a gap in current research. Instead, RNNs have been more frequently applied to grasp estimation and detection tasks, where their sequential data processing capabilities can be leveraged to predict and refine robotic actions based on a series of sensory inputs or preceding movements.

In light of these observations, Table 5 presents pioneering works that venture into using RNNs for object localization. These contributions not only signify the potential expansiveness of RNN applications beyond their traditional domains but also pave the way for further exploration into their capabilities in enhancing robotic perception and interaction within complex and dynamically changing environments. The study by Pastor et al. [64] epitomizes the theme of leveraging multimodal data to enrich object recognition capabilities in robots. By integrating tactile and kinesthetic information through LSTM neural networks, this research highlights the potential of RNNs to process sequential and spatially diverse data, leading to more nuanced and accurate object recognition. The combination of Bayesian and neural inference methods further underscores the adaptability and precision of RNNs in discerning objects based on a synthesis of different sensory inputs. This multimodal approach not only enhances the robot's ability to recognize objects with higher fidelity but also showcases the versatility of RNN architectures in handling complex data integration tasks. Ke's development of a Deep Deterministic Policy Gradient (DDPG)-based Recurrent Attention Model (RAM) for object localization embodies the innovative use of attention mechanisms within RNN frameworks [65]. This approach exemplifies how RNNs can be tailored to focus on relevant features within a scene, effectively improving localization accuracy and stability, particularly in challenging scenarios like occlusions. The incorporation of prioritized experience replay mechanisms further accentuates the efficiency of RNNs in learning from interactions, allowing for more rapid and focused improvements in object localization tasks. This theme highlights the significant strides being made in utilizing RNNs for sequential decision-making processes, enabling robots to better understand and navigate their surroundings with precision.

The nuanced application of RNNs in object pose estimation presents

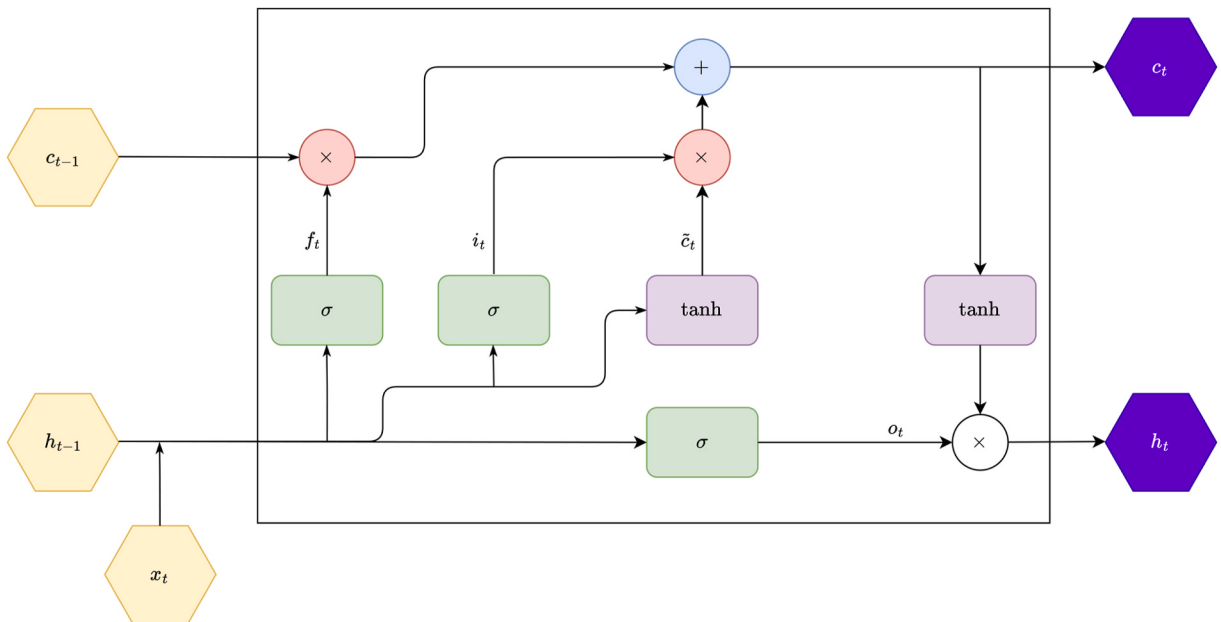


Fig. 6. The architecture of an LSTM cell, highlighting its components and the flow of information which allows for the learning of long-term dependencies essential in sequential tasks such as robotic grasping.

Table 5
Innovations in RNN applications for object localization: enhancing robotic interaction with environments. This table compiles pivotal studies employing recurrent neural networks to advance object localization, demonstrating how these techniques bolster robotic systems’ ability to navigate and interact with their surroundings effectively.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Pastor et al. [64]	2020	Multimodal Object Recognition from Tactile and Kinesthetic Information	Developed an LSTM-based neural network model for object recognition combining tactile and kinesthetic data, demonstrating the effectiveness of Bayesian and neural inference for improving object recognition capabilities.	LSTM Neural Networks, Tactile and Kinesthetic Information Fusion
Ke [65]	2020	Object Localization with Recurrent Attention Model	Introduced a DDPG-based RAM for object localization, showing significant improvements in localization accuracy and stability, especially in occlusion situations. Proposed a prioritized experience replay for enhanced learning efficiency.	DDPG-based RAM, Prioritized Experience Replay, Object Localization Accuracy

a promising avenue for addressing complex challenges in robotic systems, especially those operating in dynamic or unstructured environments. Similar to object localization, the application of RNN in object pose estimation is relatively less explored, indicating a burgeoning field ripe with potential. Table 6 presents a collection of seminal works that have begun to tap into the power of RNNs for object pose estimation. The studies, particularly Xu et al. [66] and Preechayasomboon and Rombokas [67], illustrate the exceptional capability of RNNs to enhance robotic perception under complex scenarios like occlusions and environments with low visibility. RNNPose, introduced by Xu et al. [66], underscores the potential of RNNs in refining object poses with high accuracy, emphasizing the resilience of these networks to initial pose errors and occlusions. This advancement marks a significant step in robotic perception, enabling robots to recognize and adjust to the spatial orientation of objects even when partially obscured. Similarly, Preechayasomboon and Rombokas [67] highlight the application of RNNs in proprioception within soft robotics, leveraging fluidic actuation as a sensing medium. This innovative approach broadens the scope of

robotic perception, particularly in environments where traditional sensing methods may falter. Tanaka et al. [68] contribute to a novel methodology within the RNN domain by focusing on the pose estimation of proprioceptive sensors in continuum, soft robotic arms. By employing deep reservoir computing, their work significantly advances control mechanisms in low-visibility environments, offering a new avenue for precise and adaptive control in soft robotics. This method stands as a testament to the adaptability of RNN architectures in addressing specific challenges in robotic manipulation and navigation, providing a template for future research in robotic control systems.

RNNs offer a unique advantage in grasp estimation and detection by leveraging their inherent ability to remember and integrate information over time. Despite the focus of many studies on using RNNs primarily for sequence prediction tasks, their application in the domain of robotic grasp estimation and detection has started to gain traction. This emerging trend is reflected in the diversity of approaches explored in recent research, from enhancing the accuracy of grip force prediction to optimizing grasping strategies for multifingered robotic hands. These developments signify a broader recognition of the potential of RNNs to revolutionize how robots interact with their environment, making them more responsive, intelligent, and capable of executing complex manipulation tasks autonomously. Table 7 highlights significant contributions in the field of robotic grasp estimation and detection utilizing RNNs. These studies showcase the versatility and efficacy of RNNs in improving robotic grasping capabilities, underscoring their pivotal role in advancing robotic manipulation towards more sophisticated and autonomous systems. A significant theme emerging from these studies, such as those by Ayral et al. [69] and Wong et al. [70], centers on the enhancement of robotic sensory intelligence. Through the development of spectro-temporal RNN models for slip detection and the combination of LSTM with CNN networks for dynamic object grasping, RNNs are pivotal in equipping robots with the ability to detect and react to physical interactions with high precision and reliability. These advancements underline the critical role of RNNs in refining robotic perception and tactile feedback mechanisms, ensuring more stable and adaptable manipulation capabilities. Research exemplified by Ghorbani Siavashani et al. [71] and Khin et al. [72] explores the application of RNNs in predicting grip force from sEMG signals and estimating grip stability in soft robotics. These studies demonstrate the potential of RNNs to revolutionize control mechanisms in prosthetics and soft robotic systems, offering enhanced adaptability and functionality. By leveraging RNNs’ ability to process sequential and temporal data, these works open new pathways for developing more intuitive and responsive control systems in robotic manipulation. Kawaharazuka et al. [73] and Marban et al. [74] contribute to the innovation in object recognition and dynamic contact control, as well as force estimation in contexts such as robotic surgery. The use of integrated RNN approaches and hybrid CNN-RNN models in these areas highlights the versatility of RNNs in handling complex sensory inputs and generating precise control outputs. These contributions are instrumental in advancing robotic capabilities in environments requiring delicate and precise manipulations.

Table 6
Pioneering applications of RNNs in object pose estimation: bridging the gap in robotic perception and interaction. This table showcases innovative RNN applications in object pose estimation, illustrating the nuanced contributions of these models to understanding objects’ spatial orientation for enhanced robotic manipulation and navigation.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Xu et al. [66]	2024	RNNPose: 6-DoF Pose Estimation	Introduced RNNPose, an RNN-based framework for refining object poses with robustness to occlusions and initial pose errors, showing state-of-the-art performance on public datasets.	Recurrent Correspondence Field Estimation, Pose Optimization, Consistency-Check Mechanism
Tanaka et al. [68]	2022	Continuum-Body-Pose Estimation with RNNs	Demonstrated a novel method for pose estimation of proprioceptive sensors in soft robotic arms using RNNs, significantly enhancing control in low-visibility environments.	Deep Reservoir Computing, Proprioceptive Sensor Pose Estimation
Preechayasomboon and Rombokas [67]	2023	Soft Robotic Proprioception with RNNs	Presented a method for deriving soft actuator poses using RNNs, leveraging the actuating fluid as a sensing medium for proprioception.	Recurrent Neural Networks, Soft Actuator Proprioception

Table 7
Exploring the frontier of recurrent neural networks for grasp estimation and detection: a leap towards robotic dexterity and sensory intelligence. This table consolidates pioneering research that integrates RNNs to enhance grasp estimation and detection, underscoring their vital role in advancing robotic manipulation and interaction with complex environments.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Ayral et al. [69]	2023	Robotic Slip Detection	Developed a spectro-temporal RNN model for slip detection using piezoelectric sensors, achieving high classification accuracy and demonstrating potential for enhancing robotic manipulation reliability.	Spectral analysis, GRU networks
Ghorbani Siavashani et al. [71]	2023	Grip Force Prediction	Demonstrated the effectiveness of RNNs in predicting grip force from sEMG signals, significantly outperforming traditional methods and offering potential in prosthetic control.	GRU, LSTM networks
Wong et al. [70]	2022	Dynamic Object Grasping	Combined LSTM and CNN networks for predicting and grasping moving objects, improving the adaptability of robotic manipulators in dynamic environments.	LSTM, CNN networks
Khin et al. [72]	2021	Grasp Stability in Soft Robotics	Integrated flexible sensors with RNNs to estimate grip stability in a soft robotic hand, showing promise for adaptive grasping mechanisms.	LSTM networks, One-shot learning
Kawaharazuka et al. [73]	2020	Flexible Musculoskeletal Hand Control	Proposed an integrated RNN approach for object recognition and dynamic contact control in musculoskeletal hands, demonstrating adaptability to hand model changes over time.	RNN with parametric bias
Chen et al. [75]	2020	Fingertip Force Estimation	Utilized RNNs alongside other algorithms to estimate forces and torques from fingernail images, contributing to the field of human grasp analysis.	Gaussian processes, CNNs, RNNs
Marban et al. [74]	2019	Force Estimation in Robotic Surgery	Presented a hybrid CNN-RNN model to estimate forces in robotic surgery without direct force sensors, aiming to improve surgical safety and efficacy.	CNNs, LSTM networks
Michaels et al. [76]	2019	Grasp Movement Generation	Explored modular RNNs for simulating grasp movement generation, offering insights into the interplay between visual inputs and motor outputs in grasping.	Modular RNNs
Arapi et al. [77]	2018	Hand Manipulation Strategy Labeling	Introduced a deep learning method for identifying hand manipulation strategies from video, combining CNNs for hand detection and RNNs for action prediction, achieving up to 94 % accuracy.	CNNs, RNNs
Xia et al. [78]	2004	Grasping-force Optimization	Introduced an RNN-based model for real-time optimization of grasping forces, enhancing the dexterity and effectiveness of robotic hands.	RNNs

3.6. RL models for adaptive grasping

ML is not a monolith but a mosaic, offering a spectrum of methodologies like supervised, unsupervised, semi-supervised, self-supervised, and RL, each with distinct characteristics and domains of applicability, as depicted in Fig. 7. While supervised learning [79] thrives on labeled datasets to generalize from known to unknown instances, it is inherently limited by the quality and quantity of these labels, constraining its performance to the Bayes error rate. On the other hand, unsupervised learning [80] seeks to unveil hidden structures within unlabeled datasets, proving instrumental in clustering, dimensional reduction, and feature extraction [81–83]. Semi-supervised learning blends elements from both paradigms, leveraging a small subset of labeled data complemented by a larger pool of unlabeled data, offering advantages in scenarios like fault detection [84–87] where acquiring labels is cost-prohibitive. Emerging from the realms of unsupervised learning, self-supervised learning [88–90] ingeniously generates its labels from the data itself, paving the way for supervised models without the need

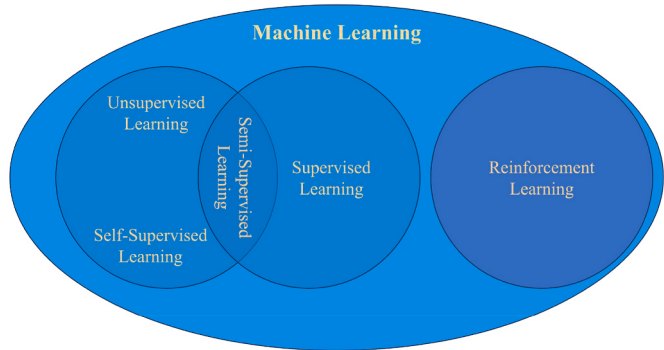


Fig. 7. Overview of the diverse landscape of machine learning methodologies. This diagram delineates the primary sub-components of ML, showcasing the spectrum from supervised to unsupervised learning, and highlighting the specialized roles of semi-supervised, self-supervised, and reinforcement learning. Each branch represents a unique approach to learning from data, whether labeled or unlabeled, structured or unstructured, offering tailored solutions for a wide array of computational tasks and challenges.

for manual labeling.

Transitioning from these traditional paradigms, RL marks a paradigm shift, striving to learn optimal policies through trial-and-error interactions with the environment, steered by a reward signal [23,91–93]. In contrast to the supervised paradigms, RL is characterized by sequential decision-making, where an agent learns to navigate a possibly stochastic environment, balancing the need for exploration and exploitation. This balance is pivotal, especially in dynamic or uncertain systems [94,95], where the agent must choose between exploiting known rewards and exploring new possibilities to maximize the long-term return.

Model-Based Reinforcement Learning (MBRL) stands out for its strategic approach. MBRL constructs an explicit model of the environment, using it to predict future states and rewards [96,97]. This predictive capability allows for informed decision-making and planning, making it particularly advantageous in complex environments where interactions are expensive or risky. MBRL’s ability to anticipate and simulate future states opens doors to more efficient learning and planning strategies, especially in domains where real-world interaction is limited or costly.

Complementing MBRL, Value-Based Reinforcement Learning (VBRL) seeks to estimate the value of each state or state-action pair, representing the expected return from that state or state-action pair onwards [98,99]. By iteratively improving these value estimates, VBRL algorithms converge to optimal policies that maximize the expected return. VBRL’s strength lies in its robustness and simplicity, especially in environments with discrete, finite action spaces. However, scaling VBRL to high-dimensional or continuous action spaces often necessitates sophisticated function approximation techniques.

Policy-Based Reinforcement Learning (PBRL), on the other hand, directly parameterizes and optimizes the policy, offering a more nuanced control over the actions, particularly in environments with continuous or high-dimensional action spaces [100–103]. PBRL’s direct approach to learning the policy enables a more straightforward handling of complex action spaces and stochastic policies. However, this directness comes with its challenges, such as high variance in policy gradient estimates and the need for efficient exploration strategies.

3.6.1. Fundamentals of RL

RL stands as a sophisticated computational paradigm, aimed at the understanding and automation of goal-directed learning and decision-making. It is distinctively characterized by an agent that learns to navigate an environment through executing actions and observing their consequent results. The RL framework is commonly formalized utilizing the MDP model, which offers a structured mathematical approach for modeling decision-making scenarios where outcomes are influenced by a combination of random factors and the decision-maker's control. This section delves into the RL problem's formal representation via the MDP framework, shedding light on its principal components, including states, actions, rewards, and policies. Furthermore, it discusses the learning objectives encompassing various optimality criteria.

At the core of RL, MDPs provide a robust framework for depicting the interaction between an agent and its environment in stochastic contexts. An MDP formalizes the sequence of decision-making by capturing the environment's state, available actions to the agent, transition probabilities, and the reward structure.

An MDP is defined as a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{T}, \mathcal{R})$, where:

- $\mathcal{S}$ represents the set of all potential environmental states. In finite MDPs, $|\mathcal{S}| = N$, with each state $s_t \in \mathcal{S}$ encapsulating the requisite information from the environment for decision-making at any given instance.
- $\mathcal{A}$ signifies the set of all possible actions the agent can undertake. Analogous to the state space, for a finite set of actions, $|\mathcal{A}| = K$.
- $\mathcal{T} : \mathcal{S} \times \mathcal{A} \times \mathcal{S} \rightarrow [0, 1]$ is the state transition function, delineating the environment dynamics. For any state-action pair (s, a) , $\mathcal{T}(s, a, s')$ provides the transition probability to state s' .
- $\mathcal{R} : \mathcal{S} \times \mathcal{A} \rightarrow \mathbb{R}$ is the reward function, offering immediate feedback for each action executed in a particular state, thereby guiding the agent's learning trajectory.

MDP dynamics are inherently Markovian, implying that the upcoming state depends solely on the current state and the action executed, rather than the preceding sequence of events. This Markov property is instrumental in simplifying the complexity of decision-making, thereby enabling the feasibility of diverse solution methods.

At each timestep t , the agent observes state $s_t \in \mathcal{S}$, chooses an action $a_t \in \mathcal{A}$ based on policy π , receives a reward $r_t = \mathcal{R}(s_t, a_t)$, and transitions to a new state s_{t+1} with a probability $\mathcal{T}(s_t, a_t, s_{t+1})$.

The primary objective within an MDP is to discover an optimal policy π^* that maximizes the anticipated cumulative reward over time. This is generally expressed as formulating a policy that maximizes the expected return, where the return G_t is defined as the discounted sum of future rewards:

$$G_t = \sum_{k=0}^{\infty} \gamma^k r_{t+k+1} \quad (5)$$

here, $\gamma \in [0, 1]$ represents the discount factor, quantifying the present value of future rewards.

3.6.2. RL in grasping

RL, and particularly its extension into Deep Reinforcement Learning (DRL), has emerged as a transformative approach for imbuing robotic systems with the ability to autonomously refine and enhance their grasping capabilities [104]. This paradigm shift leverages the iterative nature of RL to evolve grasping strategies that are both effective and efficient, underpinned by a reward structure that incentivizes successful outcomes.

The complexity of robotic grasping stems from the intricate interplay between object recognition, pose estimation, and the physical dynamics of manipulation. Traditional methods, often reliant on explicit programming and rule-based algorithms, struggle to accommodate the vast array of variables and uncertainties inherent in real-world tasks. DRL, by contrast, thrives in such environments by employing neural networks to

process high-dimensional sensory input, enabling a robot to learn grasp strategies through continuous interaction with its environment.

A pivotal advancement facilitated by DRL in robotic grasping is the seamless integration of perception and action. Through the utilization of CNNs within the RL framework, robots can now interpret complex visual inputs to make informed decisions about how to adjust their grip, angle, and force when grasping objects of varying shapes, sizes, and textures. This integration allows for a more nuanced understanding of the environment, surpassing the limitations of pre-programmed approaches.

By defining rewards that correspond to successful grasps and penalties for failures, robots are encouraged to explore and exploit different strategies to maximize their cumulative reward. This process fosters the development of innovative grasping techniques that might not have been conceived through conventional programming methods. Importantly, the flexibility of the reward structure in RL enables customization to prioritize specific aspects of grasping, such as minimizing time, energy consumption, or maximizing grip stability.

Table 8 encapsulates significant research efforts and breakthroughs in the utilization of RL methodologies to enhance object localization capabilities in robotics. The studies, notably those by Chen et al. [105] and Kerzel and Wermter [106], emphasize the integration of deep learning techniques like YOLO with RL methodologies such as the Soft Actor-Critic algorithm. This combination is pivotal in advancing robotic grasping capabilities, allowing for the successful identification and manipulation of unseen objects. This theme underscores the trend towards merging RL with deep learning to create self-learning systems that can adapt to and navigate complex, dynamic environments more effectively. The work of Pankert and Hutter [107], alongside Azulay et al. [108], showcases the application of RL in achieving high precision in object localization and task-specific actions like assembly and object insertion. These studies highlight the capacity of RL to refine the control and feedback mechanisms of robots, enabling them to perform delicate tasks with a high degree of accuracy, even under uncertainties. This precision is crucial for applications requiring meticulous handling and placement of objects. Chen et al. [105] also highlight the significance of sim-to-real transfer techniques in the context of RL. This approach facilitates the transition of learned behaviors from simulated environments to real-world applications, thereby mitigating the challenges associated with direct training in complex real-world scenarios. This theme reflects the broader effort to leverage simulation as a scalable and efficient training ground for developing sophisticated RL policies that can be effectively applied in the physical world. Azulay et al. [108] introduce the concept of haptic glances, which involve using compliant robotic hands for object manipulation, guided by RL policies. This exploration of novel interaction modalities indicates a move towards more versatile and sensitive robotic systems that can leverage various forms of sensory feedback for enhanced object localization and manipulation. Lastly, the study by Weber et al. [109] provides a look back at the foundational work in combining neural networks with RL for tasks like robotic docking. It showcases the long-term trajectory of RL research in robotics, highlighting the continuous evolution of methodologies that combine perception, learning, and control to improve robotic interaction and efficiency in diverse tasks.

Table 9 presents a curated collection of pioneering studies that exemplify the fusion of RL with Object Pose Estimation, illustrating the novel strategies and technologies that propel robots toward achieving higher levels of autonomy and efficiency. By focusing on these developments, we can discern several key themes that illustrate the trajectory of innovation in this field. Huang et al. [110] introduce EARL, a system that leverages Eye-on-Hand coordination for active pose estimation, specifically targeting dynamic grasping of moving objects without the necessity for motion prediction. This represents a significant shift towards more responsive and adaptable systems capable of real-time adjustments based on immediate environmental feedback, highlighting the trend towards developing more autonomous and versatile robotic systems. The work of Pankert and Hutter [107] emphasizes

Table 8
Advancements in RL for object localization: enhancing robotic interaction and efficiency. This table outlines key developments in the application of RL towards improving object localization capabilities in robotics, illustrating how RL methodologies advance robotic perception and interaction in complex environments.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Chen et al. [105]	2023	Robotic Grasping via Deep RL	Introduced a self-learning approach combining YOLO for object detection with SAC algorithm for robotic manipulator control. Demonstrated successful grasping of unseen objects leveraging Sim-to-Real techniques.	YOLO, Soft Actor-Critic, Sim-to-Real
Pankert and Hutter [107]	2023	Contact-Based State Estimation	Presented a reinforcement learning-based exploration strategy for precise state estimation in assembly tasks, achieving high accuracy in object localization.	Reinforcement Learning, State Estimation
Azulay et al. [108]	2022	Haptic-Based Object Insertion	Explored haptic glances with compliant hands for object insertion, proposing an RL policy for precise control under uncertainties, validated through precision insertion tasks.	Haptic Feedback, Deep Residual Reinforcement Learning
Kerzel and Wermter [106]	2017	Self-learning Visuomotor Skills	Developed an end-to-end deep convolutional architecture for learning visuomotor skills through environmental interaction, emphasizing fast self-learning for object grasping.	Supervised End-to-End Learning, Deep Convolutional Networks
Weber et al. [109]	2003	Robotic Docking with Neural Vision	Proposed a neural network-based solution for robotic docking, combining object recognition with RL for precision in approaching and grasping tasks.	Neural Networks, Reinforcement Learning

Table 9
Innovations in reinforcement learning for object pose estimation: enhancing robotic grasping and manipulation precision. This table encapsulates pivotal advancements in merging reinforcement learning with object pose estimation to amplify precision and flexibility in robotic interactions with objects.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Huang et al. [110]	2023	Dynamic Grasping with Active Pose Estimation	Presented EARL for real-time pose tracking and dynamic grasping of moving objects using Eye-on-Hand systems, without motion prediction.	Eye-on-Hand Coordination, Active Pose Estimation, Reinforcement Learning
Pankert and Hutter [107]	2023	Contact-Based State Estimation	Proposed a RL strategy for precise object pose estimation in assembly tasks, using contact detection and kinematics.	Reinforcement Learning, Contact-Based State Estimation
Al-Shanoon et al. [111]	2022	Sequential Robotic Manipulation	Introduced a self-learning strategy for manipulating unknown-adjacent objects, combining pre-grasping and grasping actions.	Deep Reinforcement Learning, Sequential Manipulation
Shukla et al. [112]	2021	Grasp Manipulation	Developed models for pose estimation combining evolutionary computing with deep reinforcement learning.	Evolutionary Computing, Deep Reinforcement Learning
Ren et al. [113]	2021	Fast-Learning Grasping and Pre-Grasping	Proposed a framework integrating pre-grasping actions with grasping to efficiently pick objects from cluttered environments.	Deep Reinforcement Learning, Clutter Quantization, Q-map Masking
Beltran-Hernandez et al. [114]	2019	Grasping with Primitive Shaped Object Policies	Showed that RL policies trained with primitive shapes can generalize to complex shapes, enhancing robotic grasping.	Guided Policy Search, Object Policy Generalization
Piater et al. [115]	2011	Visual Representations for Action Systems	Discussed the creation of task-specific, learnable visual representations, including a direct reinforcement learning approach on visual input.	Visual Representations, Reinforcement Learning, Perception-Action Systems

the importance of precise state estimation in assembly tasks through RL strategies that exploit contact detection and kinematics. This approach underscores the growing emphasis on integrating sensory feedback into RL frameworks to refine pose estimation and manipulation strategies, catering to the intricate requirements of industrial applications. Al-Shanoon et al. [111] and Shukla et al. [112] demonstrate an evolution towards sequential manipulation strategies and task-specific learning. These studies reveal a move towards systems that not only learn optimal grasping actions but also how to manipulate objects in a sequence of actions, enhancing the robot’s ability to interact with complex, unstructured environments. Ren et al. [113] introduce a framework that integrates pre-grasping actions with grasping, illustrating an important advancement in using RL to develop more efficient strategies for object interaction, particularly in cluttered environments. This highlights the potential for RL to optimize robotic actions in a more holistic manner, considering both the approach to an object and the grasp itself. Beltran-Hernandez et al. [114] showcase how RL policies trained with primitive shapes can be generalized to complex shapes, addressing one of the significant challenges in robotic grasping—the diversity of object shapes and sizes. This research points towards the broader applicability of RL-trained models across a range of objects, improving the versatility of robotic systems. Finally, the foundational work of Piater et al. [115] explores creating task-specific, learnable visual representations, integrating direct reinforcement learning approaches on visual inputs. This early exploration lays the groundwork for the convergence of perception and action systems within RL frameworks, emphasizing the critical role of visual data in informing robotic actions.

The advancements in RL for grasp estimation and detection

underscore a vibrant area of research that significantly impacts robotic precision and efficiency. By examining these studies collectively, as illustrated in Table 10, several cohesive themes emerge, each contributing to the evolution of robotic grasping capabilities. A notable theme, as demonstrated by Zhu et al. [116], is the focus on improving sample efficiency through the application of equivariant models. This approach allows for more effective end-to-end training regimes by leveraging the inherent symmetries in robotic grasping tasks. Such advancements in training methodologies not only reduce the required amount of training data but also speed up the learning process, making it more feasible to train robots for complex grasping tasks. Liu and Howe [117] introduce a novel framework for incorporating stochastic models of friction into robotic grasping, which marks a significant shift towards more realistic and adaptable simulation models. This development enhances the ability of RL algorithms to account for the variability and uncertainty inherent in real-world environments, thus improving the sim-to-real transfer capabilities and overall robustness of robotic grasping systems. The work by Liu et al. [118] on collaborative viewpoint adjusting and grasping through deep reinforcement learning illustrates a trend towards developing more dynamic and adaptable strategies for robotic manipulation. By integrating multiple aspects of a task, such as viewpoint adjustment and object grasping into a unified strategy, robots can better navigate and interact with cluttered or complex environments, thereby improving grasp success rates. Gonnochenko et al. [119] showcase the application of deep reinforcement learning in a real-world task of coin bag manipulation, highlighting the potential of RL in practical applications. This study, along with others focusing on optimizing robotic grasping with algorithms like Gaussian-DDPG (Zhang et al. [120]), points towards a growing trend of integrating custom

Table 10

Advancements in RL applications for grasp estimation and detection: elevating robotic precision and efficiency. This table delineates the significant strides made through the application of RL in grasp estimation and detection, showcasing how these methodologies refine robotic interactions with objects by enhancing precision, adaptability, and learning from interactions.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Zhu et al. [116]	2023	Robot Grasp Learning using Equivariant Models	Demonstrated the use of SE (2)-equivariant structures in neural networks to improve sample efficiency and enable end-to-end training for robotic grasping. Presented a framework for modeling friction as a distribution, enhancing reinforcement learning and sim-to-real transfer for robotic grasping. Developed a deep reinforcement learning strategy for coordinating viewpoint adjusting and grasping, improving success rates in cluttered environments.	Equivariant Models, Sample Efficiency Improvement
Liu and Howe [117]	2023	Stochastic Friction Models for Grasping	Presented a framework for modeling friction as a distribution, enhancing reinforcement learning and sim-to-real transfer for robotic grasping. Developed a deep reinforcement learning strategy for coordinating viewpoint adjusting and grasping, improving success rates in cluttered environments.	Stochastic Friction Models, Enhanced RL
Liu et al. [118]	2022	Collaborative Viewpoint Adjusting and Grasping	Developed a deep reinforcement learning strategy for coordinating viewpoint adjusting and grasping, improving success rates in cluttered environments.	Deep Reinforcement Learning, Collaborative Strategy
Gonnochenko et al. [119]	2021	Intelligent Robotic Coin Bag Manipulation	Applied deep reinforcement learning for autonomous coin bag manipulation, demonstrating high success rates in real-world settings with a custom gripper design. Improved the deep reinforcement learning algorithm for robotic grasping, addressing unknown disturbances and enhancing grasping efficiency.	Deep Reinforcement Learning, Real-world Application
Zhang et al. [120]	2021	Robot Grasping Optimization with DDPG	Improved the deep reinforcement learning algorithm for robotic grasping, addressing unknown disturbances and enhancing grasping efficiency.	Deep Reinforcement Learning, Gaussian-DDPG
Pedersen et al. [122]	2020	Transferring DRL Grasping Agent	Proposed a novel approach combining DRL, GANs, and visual servoing to transfer learning from simulation to real-world grasping tasks. Introduced an active exploration	DRL, GANs, Visual Servoing
Liu et al. [121]	2019	Active Affordance Exploration	Introduced an active exploration	Active Exploration, Deep

Table 10 (continued)

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
			framework with a deep reinforcement learning method, showcasing a novel composite hand for improved robotic grasp efficiency.	Reinforcement Learning

hardware designs and RL algorithms to address specific real-world challenges. Active exploration and the utilization of affordance learning, as seen in Liu et al.'s introduction of a novel exploration framework, emphasize the importance of interactive learning environments [121]. By actively exploring their surroundings, robots can autonomously discover and leverage affordances, leading to more efficient and adaptable grasping capabilities. Pedersen et al. [122] propose a combined approach of DRL, GANs, and visual servoing for transferring a grasping agent from simulation to real-world tasks, embodying the crucial theme of cross-domain adaptation. This highlights the importance of transfer learning in overcoming the challenges of domain gaps, enabling robots to apply learned skills in varied and unstructured environments.

3.7. Transfer learning models for adaptive grasping

Transfer learning has emerged as a pivotal technique in robotics, particularly in enhancing the adaptability and efficiency of grasping mechanisms in space environments. This approach leverages knowledge gained from one task to improve learning or performance in a related but distinct task. Given the unique challenges of space, including micro-gravity conditions, dynamic lighting, and the presence of unstructured or unfamiliar objects, transfer learning enables robots to quickly adapt to these new scenarios, utilizing pre-learned knowledge to reduce the learning curve. Additionally, collecting extensive labeled datasets in space conditions is impractical. Transfer learning allows for the utilization of data or models pre-trained in Earth-based or simulated environments, making the most out of limited data available in space. Moreover, the ability to transfer knowledge from diverse training environments enhances the robustness of grasping models, making them more reliable under the variable conditions found in space.

Before leveraging the power of transfer learning, it is crucial to carefully pre-process the available data. This step ensures that the input data, whether from Earth-based labs, simulations, or limited space missions, is consistent and optimized for learning. Data pre-processing in space robotic systems often includes normalization, augmentation, and encoding steps to simulate or mimic the conditions encountered in space. This preparation phase is vital for bridging the gap between terrestrial and extraterrestrial environments, allowing for a smoother knowledge transfer.

The heart of transfer learning lies in utilizing pre-trained CNN models, which have been previously trained on large, diverse datasets such as ImageNet. These models, equipped with learned features that can generalize across various tasks, offer a robust foundation for further training. In the context of robotic grasp detection, pre-trained models are fine-tuned with domain-specific data, which in the case of space robotics, might be sparse or limited. This fine-tuning process adjusts the weights of the neural network to better suit the specific requirements of grasping tasks in space, significantly reducing the risk of overfitting despite the smaller dataset size.

The literature points to instances where transfer learning has enabled robotic systems to achieve near 90 % accuracy in grasp detection tasks [14]. This level of performance is particularly impressive given the

constraints of operating in space, such as microgravity and the necessity for robots to deal with objects of unknown shapes and compositions. However, the journey to achieving such accuracies underscores the importance of choosing the right pre-trained model and the intricacies involved in fine-tuning these models to align with the specifics of space-related tasks.

Additionally, Transfer Learning, when applied to RL, can significantly reduce sample complexity and accelerate the learning process. The research by Pinto et al. serves as a prime example of how RL principles can be effectively utilized within the realm of transfer learning for robotic grasping [123]. In their approach, RL enables robots to develop skills through environmental interactions. Pinto et al. adopt a self-supervised, data-driven strategy—a core aspect of RL—to compile a comprehensive dataset that forms the basis for model training. This approach reflects the RL strategy of learning from a broad spectrum of experiences, facilitating the system's ability to identify graspable points on objects, which is crucial for robotic functionality.

The unsupervised data collection method used by Pinto et al. [123] mirrors the exploration phase in RL, wherein an agent interacts with its environment to accumulate experience. This methodology is depicted in Fig. 8, where the neural network architecture is configured to output binary classifications for various grasp angles, similar to how an RL agent evaluates different actions. Through a multi-stage learning process, the model iteratively enhances its grasp prediction policy, analogous to an RL agent refining its action policy. The self-supervision technique adeptly embodies the trial-and-error essence of RL, autonomously generating labeled data points, thus overcoming the challenges associated with manual labeling and ensuring system robustness for practical applications.

This innovative approach not only enables the system to learn from successful grasps but also to adapt from unsuccessful attempts, thereby expanding the dataset and improving the model's grasp prediction accuracy.

3.7.1. Recent advancements

Recent advancements in transfer learning for robotic grasping have been instrumental in pushing the boundaries of what is achievable in space robotics. Tables 11–13 encapsulate these advancements, highlighting key contributions across various facets of grasping, including object localization, pose estimation, and direct grasp detection.

Understanding the advancements in transfer learning for object localization in robotics involves looking at how these technologies push the boundaries of what's possible in robotic perception and interaction. Detailed exploration of the synergies and forward-looking implications of the works is presented in Table 11. A recurring theme across these studies, particularly evident in the works of Lu et al. [124] and Sui et al. [126], is the emphasis on overcoming the sim-to-real gap. This challenge is central to robotics, where models trained in simulated environments often fail to perform as expected in the real world due to the differences between simulated and real sensory data. By employing strategies such as domain randomization (Lu et al. [124]) and the generation of synthetic training samples (Sui et al. [126]), these studies underscore the importance and effectiveness of transfer learning in enabling robots to adapt to the complexities of real-world operations. Another significant advancement is the integration of multi-modal data to improve object localization, as seen in the work of Wu et al. [127]. By fusing RGB-D data for object detection and employing transfer learning with sophisticated neural network architectures like Inception-v3, this research highlights the potential of leveraging diverse data sources to refine the robot's perception. Such integration allows for more accurate and reliable object localization, essential for tasks requiring precise manipulation and interaction. The adaptability of robotic systems to new or changing environments is further exemplified in the active learning-based approach by Fu et al. [125]. Here, the focus shifts towards creating robotic systems that can learn and adapt on-the-fly, reducing reliance on extensive pre-programmed knowledge and manual intervention. This adaptability, facilitated by transfer learning, is crucial for robots operating in dynamic environments where conditions and requirements can change rapidly. The precise localization and grasping of objects, as demonstrated by Farag et al. [46], represent critical capabilities for robotic systems, especially in industrial and logistics applications. The integration of deep learning techniques for real-time object detection and the strategic application of transfer learning to refine these models based on domain-specific data are indicative of the strides being made towards achieving high levels of precision and efficiency in robotic tasks.

Table 12 underscores the innovative methods developed to address the complexities of accurately determining the orientation and position of objects for effective robotic manipulation. This synthesis of research highlights a broad spectrum of approaches, each contributing uniquely

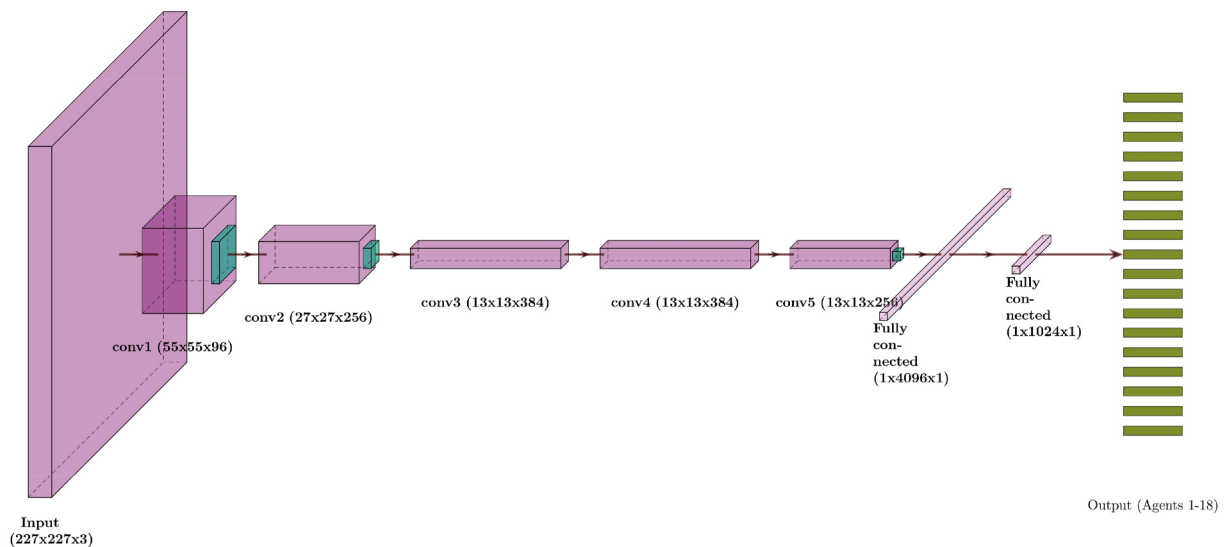


Fig. 8. An eighteen-way binary classifier by Pinto et al. [123] demonstrating a sophisticated neural network architecture. It begins with an input layer tailored for images of 227×227 pixels across three channels, progressing through several convolutional layers (Conv1 to Conv5) followed by pooling layers. These layers systematically decrease spatial dimensions while deepening feature abstraction. The convolutional segments lead to two fully connected layers (Fc1 and Fc2) for high-level feature integration. Uniquely, this architecture directs the output from Fc2 to a series of 18 vertically structured agent blocks, illustrating the network's specialized design for multiple grasp angle assessments.

Table 11
Advancements in transfer learning applications for object localization: enhancing robotic interaction and precision. This table outlines key contributions in leveraging transfer learning for object localization, illustrating how this approach bolsters robotic systems’ adaptability and accuracy in diverse settings.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Lu et al. [124]	2022	Keypoint Optimization for Pose Estimation	Proposed a keypoint optimization method for robust visual detection and localization of robotic manipulators. Utilized synthetic data for DNN training and domain randomization for sim-to-real transfer, significantly improving detection performance and application in various robotic tasks.	Keypoint Detection, Sim-to-Real Transfer, Domain Randomization
Fu et al. [125]	2019	Active Learning-Based Grasp	Developed an active learning-based grasp method integrating active perception and manipulation for industrial applications. Achieved high accuracy in object localization and manipulation without prior knowledge of camera parameters or manual feature design. Demonstrated the ability to adapt to new tasks with minimal human intervention.	Active Learning, CNN, Interactive Perception
Sui et al. [126]	2019	Transfer of Robot Perception Module	Introduced two approaches based on DANN and GAN for transferring robot perception modules from simulated to real-world data. Demonstrated effective domain adaptation with minimal performance decline in real-world applications, emphasizing the generation of synthetic samples for training.	Domain Adversarial Neural Networks, Generative Adversarial Networks, Domain Adaptation
Farag et al. [46]	2019	Real-Time Robotic Grasping and Localization	Utilized a deep learning-based object detection technique, KSSnet, for real-time object localization and robotic grasping. Achieved 100 % precision in object detection and grasping accuracy, demonstrating the efficiency of combining CNN with edge detection for precise localization.	Deep CNN (KSSnet), Edge Detection, SCARA Robot
Wu et al. [127]	2018	RGB-D Sensors for Object Detection	Proposed a method using RGB-D information fusion for object detection to facilitate soft robotic manipulation. Utilized ORB-SLAM2 for environmental scanning and ICP for object localization, combined with Inception-v3 and transfer learning for recognition.	RGB-D Fusion, Object Detection, Inception-v3

to the field. Cao et al. [130] with their 6IMPOSE framework and Qian et al. [129] through CCM Pixel-DA, showcase methodologies that not only adapt models trained in simulations for use in the physical world but also preserve crucial structural and semantic information during this transition. This ensures that robotic systems maintain high levels of performance and reliability, regardless of the environment. The works of Yu et al. [128] and Mu et al. [134] have focused on enhancing self-supervision and learning efficiency to reduce reliance on large annotated datasets. These methods enable robots to learn from their interactions with the environment, iteratively improving their understanding of object poses without the need for extensive manual labeling. Yang et al.’s introduction of a tactile-based object perception framework emphasizes the potential of using tactile information alongside, or as an alternative to, visual data for pose estimation [131]. This approach is particularly beneficial for scenarios where visual occlusion or the complexity of the object’s surface makes traditional vision-based methods less effective. Zhao et al. [132] focus on improving the efficiency of pose estimation processes by refining the Mask R-CNN framework with a MobileNet backbone. This adaptation signifies a move towards models that are not only accurate but also lightweight and fast enough for real-time robotic applications, addressing the critical demand for speed in automated systems. The introduction of ViHOPE by Li et al. [133], which combines visuotactile data with shape completion, represents a novel approach to improving the accuracy of 6D pose estimation. By reconstructing a complete model of the object in-hand, this method provides a more detailed understanding, crucial for precise manipulation tasks. Shi et al.’s development of an uncertainty quantification method tackles the challenge of ensuring reliability in pose estimation [136]. By employing ensemble models, this approach offers a way to assess and mitigate the uncertainty inherent in predicting the pose of objects, enhancing the dependability of robotic grasping actions. These works and other presented works in Table 12 showcase the dynamic and multifaceted approaches being explored in the field of transfer learning for object pose estimation. From enhancing the efficiency and adaptability of models to leveraging new data sources and addressing uncertainties, these advancements are paving the way for more sophisticated and capable robotic systems capable of navigating the complexities of real-world environments.

In examining the contributions to transfer learning in robotic grasp detection and estimation, we can distill the advancements into several key themes that underscore the strides being made in this domain (Table 13). Yu et al. [128] represent a forward leap in leveraging

self-supervised learning to enhance grasp detection capabilities without relying on extensively labeled datasets. The development of SCNet for category-level object pose estimation marks a significant achievement in enabling robots to understand and interact with a wider range of objects based on generalized categories. This approach mitigates one of the primary bottlenecks in robotic learning - the scarcity of labeled data - and exemplifies the move towards more autonomous learning mechanisms in robotics. Lu et al. [124] and Liu et al. [138] both underscore the critical role of sim-to-real transfer techniques in bridging the gap between synthetic training environments and real-world applications. By utilizing strategies such as domain randomization and digital twins, these studies demonstrate how robotic systems can be prepped for real-world interaction through simulated experiences. This not only accelerates the training process but also significantly enhances the adaptability of robotic systems to diverse and unpredictable real-world scenarios. Luo et al.’s work on improving the Faster-RCNN model for grasp detection introduces a novel approach to grasp rectangle representation and region proposal [139]. This represents a shift towards optimizing existing deep learning architectures to better suit the unique requirements of robotic grasping - a crucial step for increasing the success rates and reliability of robotic manipulators in practical settings. The study by Liarokapis et al. [140] explores the realm of learning by demonstration, showcasing how human demonstrations can serve as a valuable source of knowledge for robotic systems. This approach not only facilitates the transfer of complex manipulation skills from humans to robots but also emphasizes the importance of integrating multiple modalities of learning (visual feedback, human demonstration) to enhance the grasping capabilities of robots.

4. Datasets and simulation environments

The evolution of deep learning for robotic grasping is significantly influenced by the availability and application of specialized datasets and simulation environments. These tools are indispensable for training, testing, and refining deep learning models, thereby enhancing their efficacy and reliability in real-world scenarios.

4.1. Overview of critical datasets in deep learning for robotic grasping

The development and enhancement of robotic grasping capabilities through deep learning are significantly influenced by the quality, diversity, and relevance of the datasets used in model training. These

Table 12

Advancements in transfer learning for object pose estimation in robotic grasping. This table compiles significant research efforts where transfer learning has been applied to enhance object pose estimation capabilities, crucial for improving robotic grasping efficiency and adaptability.

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
Yu et al. [128]	2023	Category-Level Object Pose Estimation	Proposed SCNet for category-level object pose estimation using self-supervised learning, capable of transferring knowledge from simulation to real world, and introduced a deformation module for adapting prior point clouds to target objects.	Self-Supervised Learning, Category-Level Pose Estimation, Deformation Module
Qian et al. [129]	2023	Real-to-Sim Object Pose Estimation	Developed a novel real-to-sim domain adaptation method, CCM Pixel-DA, to preserve structural and semantic information during transfer, integrated into pose estimation networks for robotic grasping.	Pixel-Level Domain Adaptation, Real-to-Sim Transfer, Structural Preservation
Cao et al. [130]	2023	6D Pose Estimation for Robotic Grasping	Introduced 6IMPOSE, a sim-to-real framework for 6D pose estimation using synthetic data generation and a streamlined version of PVN3D, achieving high success rates in robotic grasping tasks under varying conditions.	Sim-to-Real Data Generation, 6D Pose Estimation, PVN3D Optimization
Yang et al. [131]	2023	In-Hand Object Pose Estimation	Presented a tactile-based object perception framework, including PoinTacNet for object classification and pose estimation, utilizing sim-to-real transfer for data-efficient learning.	Tactile Perception, Sim-to-Real Transfer, Object Classification and Pose Estimation
Zhao et al. [132]	2023	Gripping Pose Estimation	Improved the Mask R-CNN network for faster target recognition and	Lightweight Neural Networks, Transfer Learning, Pose

Table 12 (continued)

Study	Year	Main Focus	Key Findings/Contributions	Methodologies Covered
			pose estimation using the MobileNet backbone and transfer learning, enhancing efficiency and robustness in robotic grasping.	Estimation Efficiency
Li et al. [133]	2023	Visuotactile 6D Pose Estimation With Shape Completion	Introduced ViHOPE, a framework for 6D pose estimation with visuotactile shape completion, showing significant improvements in accuracy and sim-to-real transfer on a real-world robot platform.	Shape Completion, Visuotactile Perception, 6D Pose Estimation
Mu et al. [134]	2022	Weakly Supervised 6D Pose Estimation	Presented Weak6D, a weakly supervised model for 6D pose estimation without annotated data, utilizing an iterative annotation resolver for training with RGB-D data.	Weakly Supervised Learning, 6D Pose Estimation, Iterative Annotation Resolver
Dikhale et al. [135]	2022	VisuoTactile Pose Estimation	Proposed a method combining tactile and vision data for improved 6D pose estimation of in-hand objects, utilizing synthetic data for training and showing successful sim-to-real transfer.	VisuoTactile Data Fusion, Synthetic Data Generation, Sim-to-Real Transfer
Shi et al. [136]	2021	Uncertainty Quantification in Pose Estimation	Proposed a simple and efficient UQ method for 6-DoF pose estimation, using ensemble models for robust performance in robotic grasping tasks.	Uncertainty Quantification, Ensemble Models, 6-DoF Pose Estimation
Thalhammer et al. [137]	2021	Object Pose Estimation Under Domain Shift	Proposed PyraPose, a feature pyramid network approach for fast and accurate pose estimation under domain	Feature Pyramids, Domain Shift, Fast Pose Estimation

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Table 12 (continued)

Study	Year	Main Focus	Key Findings/ Contributions	Methodologies Covered
			shift, demonstrated through real- world grasping experiments.	

datasets provide a foundation for learning algorithms to recognize, interpret, and act upon the complex visual and sensory information necessary for effective object manipulation. This section discusses several critical datasets that have been pivotal in advancing robotic grasping technologies, including their application in space environments, where the challenges of microgravity and unstructured surroundings present unique demands on robotic systems.

1. **Cornell Grasping Dataset [141]:** A foundational resource offering images annotated with potential grasp points, facilitating the training of CNNs to identify graspable features across a variety of objects. This dataset's extensive annotations enable models to recognize diverse graspable characteristics, proving essential for developing versatile grasping algorithms.
2. **Yale-CMU-Berkeley (YCB) Object and Model Set [142]:** Provides a comprehensive collection of common household items and their 3D models, crucial for both physical and simulated grasping experiments. The rich variety of shapes, sizes, and textures available in this set allows for the comprehensive training of models adaptable to real-world scenarios.
3. **GraspNet-1Billion [143]:** A large-scale benchmark for general object grasping, featuring over a billion grasp annotations for hundreds of objects. It includes RGB-D images from varying viewpoints, significantly enriching the dataset's diversity and complexity.
4. **Dexterous Networks (Dex-Net) [144,145]:** Contains synthetic point clouds, grasp affordances, and robust grasp metrics generated using deep learning and analytic models. Dex-Net facilitates the development of algorithms capable of planning robust grasps across a wide array of objects, enhancing the adaptability and efficiency of robotic systems.

4.1.1. Datasets for space applications

5. **Astrobee Robotic FreeFlyer Grasping Dataset [146–148]:** Though not widely available, data derived from NASA's Astrobee robot, designed for operation in the International Space Station, offers insights into object manipulation in microgravity, addressing the unique challenges of space environments.
6. **Space Debris Grasping Simulations:** Synthetic datasets generated from simulations of space debris and satellite grappling scenarios. These datasets can be customized to reflect the unique conditions of space, such as lighting variations and microgravity effects on object motion, providing invaluable resources for training models for space applications.

4.2. Simulation environments in model testing and refinement

Simulation environments are invaluable in the iterative development and refinement of models for robotic grasping, particularly under the unique challenges posed by space environments such as microgravity, radiation, and extreme temperatures. These tools provide a safe, controlled, and cost-effective arena for experiments, simulating real-world physics and interactions which allow for detailed testing of robotic sensors, actuators, and control algorithms without the risk and expense of physical prototypes. This section explores the key simulation

Table 13

Advancements in transfer learning for grasp detection and estimation: enhancing robotic grasping capabilities. This table summarizes critical advancements through transfer learning in robotic grasp detection and estimation, illustrating how this strategy improves robotic systems' grasp success rates and adaptability in handling diverse objects.

Study	Year	Main Focus	Key Findings/ Contributions	Methodologies Covered
Yu et al. [128]	2023	Self-Supervised Learning for Grasp Detection	Proposed SCNet for category-level object pose estimation and grasp detection using self-supervised learning, overcoming the lack of large-scale labeled datasets and enhancing grasp task performance on Baxter robot.	Self-Supervised Learning, Category-Level Pose Estimation, SCNet
Lu et al. [124]	2022	Keypoint Optimization for Robot Manipulators	Introduced an autonomous method for defining keypoint locations on robotic manipulators, using synthetic data and domain randomization for sim-to-real transfer and improved grasp detection.	Keypoint Optimization, Sim-to-Real Transfer, Domain Randomization
Liu et al. [138]	2022	Sim-to-Real Transfer for Industrial Robot Grasping	Developed a digital twin-enabled approach for transferring DRL algorithms for industrial grasping from simulation to physical robots, establishing parallel training systems for virtual and real environments.	Digital Twin, Deep Reinforcement Learning, Sim-to-Real Transfer
Luo et al. [139]	2020	Faster Region CNN for Grasp Detection	Introduced an improved Faster-RCNN model for grasp detection that uses a five-dimensional parameter representation and an optimized RPN for tilt graspable region proposal. Achieved high detection accuracy on the Cornell Grasp Dataset using data augmentation and transfer learning.	Faster-RCNN, Region Proposal Network, Data Augmentation
Liarokapis et al. [140]	2016	Learn by Demonstration for Grasp Planning	Presented a learn by demonstration approach for robust anthropomorphic grasp planning, using human	Learn by Demonstration, Anthropomorphic Grasping, Navigation Function Models

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Table 13 (continued)

Study	Year	Main Focus	Key Findings/ Contributions	Methodologies Covered
			demonstrations for skill transfer and RGB-D cameras for online feedback.	

platforms and their roles in enhancing deep learning models for robotic grasping.

Gazebo: A highly versatile and widely used open-source robotics simulator, Gazebo offers advanced simulation capabilities with a rich set of features. It supports the simulation of complex robotic systems in 3D environments, complete with realistic physics, lighting, and textures. Particularly beneficial for testing robotic grasping mechanisms in diverse conditions, Gazebo allows for the integration of sensor data and the manipulation of virtual objects. Researchers can iterate on design and control strategies quickly, observing the outcomes in various simulated scenarios which include mimicking the handling of space debris or satellite servicing.

MuJoCo: An advanced physics engine, MuJoCo is optimized for speed and precision in simulating complex dynamic interactions involving rigid body dynamics with contacts. It is particularly popular in the robotics and biomechanics research communities for its ability to handle high degrees-of-freedom robotic systems and its efficient, stable simulations of contact dynamics. This makes MuJoCo especially useful for space robotics, where accurate simulation of contact dynamics between the robot and various objects is crucial for successful operation. The engine’s API supports several programming languages, facilitating its integration into a wide range of research workflows. Researchers can use MuJoCo to simulate the behavior of robotic grippers interacting with irregular, possibly moving objects, which is a common challenge in space missions.

V-REP (CoppeliaSim): Known for its flexibility and scalability, V-REP (now CoppeliaSim) is another comprehensive platform for robotics simulation. It supports a wide array of robots, sensors, and environmental conditions, facilitating the development of detailed robotic models and control algorithms, with support for scripting in Lua. The platform’s ability to simulate both kinematic and dynamic properties of robots makes it ideal for testing and refining grasping techniques before real-world implementation, including simulations of vacuum conditions or thermal extremes in space applications.

ROS Gazebo Integration: The integration of the Robot Operating System (ROS) with Gazebo enhances simulation realism and utility. ROS provides a robust framework for writing robot software, offering libraries and tools to help researchers develop complex and reliable robotic applications quickly. When combined with Gazebo, ROS facilitates the simulation of robotic grasping in environments that closely mimic real-world physics and interactions, crucial for testing control strategies, sensor integration, and manipulation algorithms in a realistic yet flexible simulation environment.

PyBullet: A Python module for physics simulation in robotics, games, and machine learning, PyBullet is gaining traction for its ease of use and integration with Python-based machine learning frameworks. It offers accurate rigid body simulation and supports advanced robotic functionalities, including inverse kinematics and grasping force computation. PyBullet is particularly suited for deep learning applications, allowing for rapid prototyping and testing of robotic grasping algorithms with direct feedback on performance metrics.

Unity ML-Agents: Unity Technologies’ ML-Agents Toolkit enables the training and testing of machine learning models within the Unity game development environment. This platform is notable for its high-quality graphics and physics simulation, offering a visually rich and dynamic setting for robotic grasping research. Researchers can create

detailed simulation scenarios with varied textures, lighting, and object properties, making it a powerful tool for developing and refining vision-based grasping algorithms.

Adding to this discussion, specific development workflows, as depicted in Figs. 9 and 10, illustrate the tangible applications of these simulation tools in the field. Fig. 9 presents a MATLAB-Only Workflow tailored for robotic manipulator development. This setup utilizes MATLAB exclusively for simulation modeling, employing a Rigid Body Tree for structural definition and facilitating direct hardware interaction via specialized communication interfaces. Fig. 10 broadens this perspective by introducing a MATLAB + ROS Workflow. This approach integrates the ROS to leverage enhanced simulation capabilities with Gazebo, enabling a more sophisticated deployment through a ROS node. This setup fosters advanced communication and the execution of complex control algorithms, essential for intricate robotic operations.

These simulation environments serve as crucial platforms for the development, testing, and refinement of robotic grasping models. They enable researchers to explore a wide range of scenarios and conditions, from the physics of object manipulation to the integration of complex sensory inputs, in a controlled and reproducible manner. As such, simulation plays a pivotal role in advancing robotic grasping technologies, bridging the gap between theoretical models and their practical, real-world applications.

5. Challenges in integrating machine learning with robotic grasping for space applications

The integration of machine learning into robotic grasping, particularly for space applications, has brought forth remarkable advancements, yet it also encounters specific challenges that necessitate careful consideration and innovative solutions. These challenges stem from the complexity of space environments, the diverse nature of tasks, and the inherent limitations of current technologies. This section outlines the primary challenges faced in this domain.

5.1. Handling varied textures and occlusions

Space exploration missions often involve interacting with objects of various textures and compositions, many of which may not have been

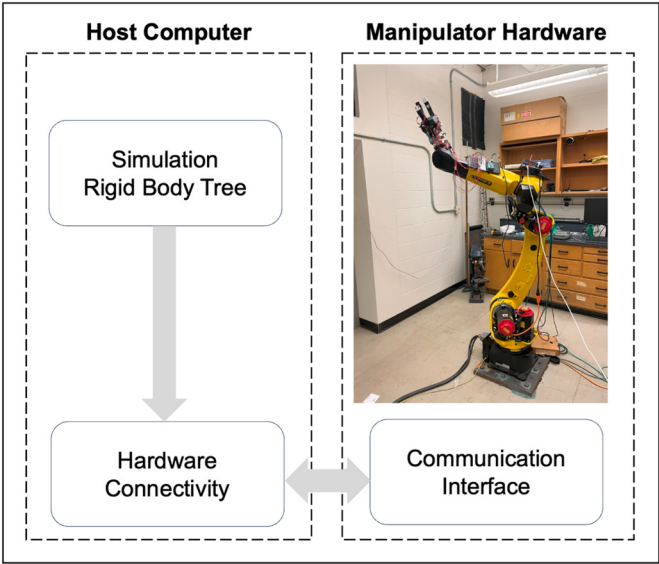


Fig. 9. The MATLAB only workflow demonstrates the utilization of MATLAB for simulation and modeling of robotic manipulators. This approach uses rigid body tree for structural analysis and ensures direct hardware connectivity for real-time testing and validation.

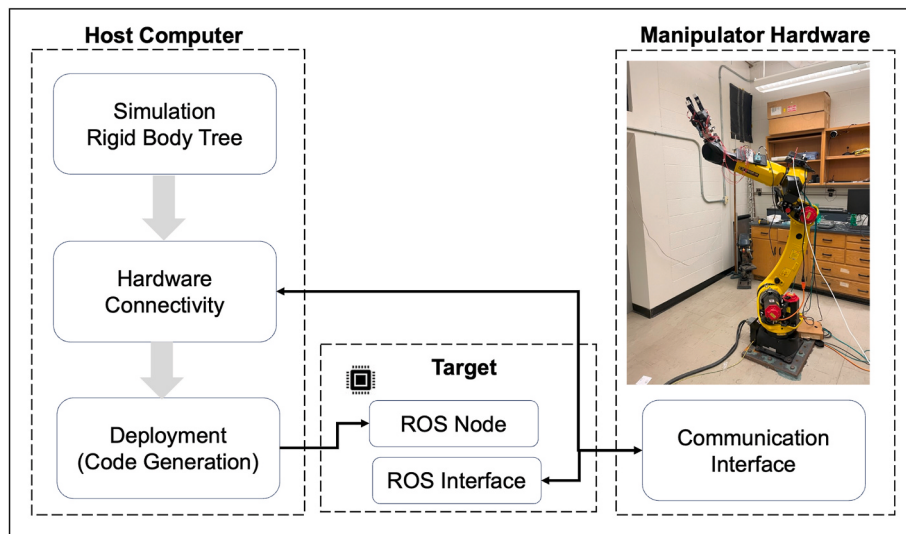


Fig. 10. The MATLAB + ROS workflow highlights an advanced simulation setup that incorporates Gazebo for a realistic environment and ROS nodes for detailed control and communication with robotic hardware. This integration facilitates complex robotic tasks and experiments in a simulated, yet highly realistic, scenario.

encountered previously. Machine learning models, especially those relying on visual data (e.g., CNNs), must contend with the challenge of accurately recognizing and estimating the pose of objects regardless of their surface properties. Additionally, potential occlusions pose a significant challenge, as critical parts of an object or its environment may be obscured, complicating the grasp estimation process.

5.2. Adaptation to unpredictable space conditions

The outer space environment introduces variables such as micro-gravity, extreme temperatures, and radiation, which can affect both the robot's functionality and the behavior of objects (e.g., floating objects). Developing machine learning models that can adapt to these conditions and predict object movement or the best grasping strategies under microgravity is a substantial challenge.

5.3. Data scarcity and simulation-to-reality gap

Collecting extensive datasets in space or environments that accurately mimic space conditions is highly impractical. While simulations offer a workaround, the gap between simulated data and real-world application (sim-to-real gap) poses a significant challenge. Machine learning models trained in simulations may not perform as expected in actual space missions due to differences in physical properties and environmental factors.

5.4. Real-time processing and decision making

For tasks such as satellite repair or sample collection, robotic systems must be capable of processing data and making decisions in real-time. The computational complexity of machine learning models, especially deep learning networks, can impede real-time processing, necessitating optimization and efficient computing strategies.

5.5. Autonomy and learning from limited interactions

Ensuring that robotic systems can learn and adapt autonomously with minimal human intervention is crucial for space missions, where communication delays or interruptions can occur. This necessitates the development of self-supervised or reinforcement learning strategies that allow robots to improve their grasping techniques through limited interactions with objects.

5.6. Integration of multimodal data

Effective robotic grasping often requires the integration of multimodal data, such as visual, tactile, and kinesthetic information. Designing machine learning models that can effectively fuse and interpret this data to improve grasp estimation and object manipulation is challenging but essential for handling the complexity of space-based tasks.

5.7. Safety and reliability

Given the high costs and significant risks associated with space missions, ensuring the safety and reliability of machine learning-driven robotic systems is paramount. Developing models that can predict and mitigate failure modes, handle unexpected situations, and ensure the safety of other space assets is a critical challenge.

6. Future directions in machine learning for robotic grasping in space applications

The exploration of machine learning in robotic grasping, particularly within the context of space applications, has revealed a landscape ripe with potential for future research and technological advancements. Building on the current foundation and addressing the outlined challenges, this section highlights key future directions that promise to propel the field toward greater achievements in autonomy, reliability, and efficiency.

6.1. Enhanced generalization through multimodal learning

Future research should prioritize the development of models capable of integrating and interpreting multimodal data more effectively. This includes not only visual information but also tactile and auditory data, providing a richer context for making grasping decisions. Advancements in this area could lead to robotic systems that adapt more fluidly to the unpredictable and varied conditions encountered in space.

6.2. Robust sim-to-real transfer techniques

Bridging the gap between simulation-based training and real-world applications remains a pivotal challenge. Future efforts could focus on creating more sophisticated simulation environments that accurately

mimic space conditions, including microgravity and material properties. Additionally, innovative transfer learning methods that can effectively adapt pre-trained models to new environments will be crucial.

6.3. Adaptive and self-supervised learning

The ability for robotic systems to learn and adapt autonomously in space is of paramount importance. Future research should explore more advanced adaptive learning algorithms and self-supervised learning mechanisms that allow robots to refine their grasping capabilities through trial and error, without the need for extensive labeled datasets.

6.4. Real-time processing and edge computing

To achieve real-time decision-making capabilities, further work is needed in optimizing machine learning models for speed and efficiency. This includes leveraging edge computing architectures where data processing occurs on or near the robotic system, reducing latency and reliance on distant computational resources.

6.5. Advanced grasp planning and execution

Future directions should also include the development of more sophisticated grasp planning algorithms that consider a broader range of factors, such as the dynamic properties of objects and the long-term consequences of different grasping strategies. Integrating predictive modeling to anticipate how objects will move or respond to contact could significantly enhance the success rate of grasps in microgravity environments.

6.6. Safety and fault tolerance

Ensuring the safety and reliability of machine learning-driven robotic systems in space will require innovative approaches to model validation, risk assessment, and failure mitigation. Future work could focus on creating models that can predict potential failure modes and autonomously adjust their actions to prevent mishaps, ensuring the safety of the mission and other space assets.

6.7. Collaborative robotics and swarm intelligence

Exploring the potential for collaborative robotic systems that can work in tandem to achieve complex tasks is a promising future direction. Leveraging swarm intelligence and cooperative learning algorithms could lead to more efficient and versatile solutions for space exploration and infrastructure development.

6.8. Ethical considerations and sustainable practices

As machine learning and robotics continue to advance, it is crucial to consider the ethical implications of these technologies, especially in the context of space exploration. Future research should incorporate sustainable practices, ensuring that space remains a safe and accessible environment for all humanity.

7. Conclusion

In conclusion, this article has provided a comprehensive exploration of the integration of ML techniques in robotic grasping, particularly emphasizing the pivotal role these technologies play in advancing robotic manipulation for space applications. Through a detailed examination of the use of deep learning, reinforcement learning, transfer learning, and neural networks, we have highlighted how these methodologies collectively enhance the autonomy, efficiency, and adaptability of robotic systems faced with the unique challenges of the outer space environment. Our discussion underscored the significant strides

made in improving robots' capabilities to perceive, interact with, and manipulate objects in space, transitioning from traditional mechanical systems to sophisticated, AI-driven mechanisms. By addressing critical challenges such as varied textures and occlusions, unpredictable space conditions, and the simulation-to-reality gap, this review has illuminated the path forward for research in this domain. It emphasized the necessity for enhanced generalization through multimodal learning, robust sim-to-real transfer techniques, adaptive and self-supervised learning strategies, and the development of collaborative robotics and swarm intelligence, all while considering ethical and sustainable practices. Furthermore, the article outlined the indispensable role of specialized datasets and simulation environments in the development, testing, and refinement of machine learning models for robotic grasping. Tools such as the Cornell Grasping Dataset and Yale-CMU-Berkeley Object, and simulation platforms like Gazebo and PyBullet were identified as critical resources that support the iterative improvement of grasping technologies. As we look to the future, it is clear that the integration of machine learning with robotic grasping holds great promise for space exploration and beyond. The advancements in this field not only pave the way for more sophisticated robotic assistants capable of conducting complex manipulation tasks in space but also foster innovations that can have far-reaching implications for robotics applications on Earth. To navigate the complexities of robotic manipulation in space effectively, continued interdisciplinary research, collaboration, and innovation are essential. By building upon the foundations laid out in this article, the research community can further unlock the potential of machine learning in transforming robotic grasping and contribute to the success of future space missions.

CRedit authorship contribution statement

Hadi Jahanshahi: Data curation, Investigation, Writing – original draft. **Zheng H. Zhu:** Conceptualization, Funding acquisition, Investigation, Supervision, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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