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REVIEW ARTICLE

Review of Autonomous Space Robotic Manipulators for On-Orbit Servicing and Active Debris Removal

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The increasing demand for on-orbit servicing (OOS) tasks, such as satellite repair, space debris removal, refueling, and upgrades, has driven the need for advanced robotic systems capable of autonomous and precise operations in space. At the core of these tasks are unmanned spacecraft equipped with robotic manipulators designed to execute critical capture and manipulation maneuvers. This paper presents a comprehensive review of space robotic missions and methodologies for effective OOS and space debris removal. It examines control strategies applied across different phases of these missions, with a focus on their implementation in 2 operational modes: free-floating and free-flying. Detailed discussions are provided on methodologies for the pre-capture phase, covering both motion planning and vision-based estimation. For the post-capture phase, the paper explores control methods designed to stabilize captured targets. Additionally, it investigates ground verification experiments, which are crucial for validating the performance of space robots under microgravity-like conditions. These experiments yield valuable insights into the dynamic behavior of space robotic systems and play an important role in advancing space robotics research. By consolidating recent advancements and identifying key technological gaps, this review highlights future research directions aimed at improving the reliability, adaptability, and safety of robotic manipulators in addressing the challenges of OOS and space debris removal.

Introduction and Background

Advancements in space technology have significantly driven the development and research of space robots, which play a vital role in assisting astronauts and performing mission-critical tasks on satellites and space stations in Earth orbit. These advancements address key challenges in space exploration, including improving astronaut safety and ensuring the long-term sustainability of space operations by reducing risks and enhancing efficiency. Among the various innovations in this field, robotic space manipulators have emerged as indispensable tools for advancing orbital operations. They are instrumental in tasks such as satellite servicing, space debris management, and the construction of space infrastructures. Robotic manipulators play a pivotal role in both current and future space missions, with the potential to revolutionize space operations. Their activities are typically divided into 4 essential phases: observation, approach (pre-capture), capture, and post-capture. Each phase demands precise control and coordination to overcome the inherent complexity and sophistication of space operations [1,2]. Transitioning successfully through these phases ensures mission success, from initially observing the target to securely capturing and manipulating it for further operations [3]. Capture targets vary significantly and can be classified as cooperative, with functional attitude and orbit control systems providing stability and safety, or noncooperative, such as tumbling satellites with unpredictable rotational axes. Additionally, targets can be collaborative, specifically designed for capture or servicing and equipped with visual markers and grapple fixtures, or noncollaborative, like most existing satellites [4]. Understanding the nature of these targets and the operational requirement of each phase is critical for optimizing robotic manipulator design and control strategies, ultimately enhancing the effectiveness and reliability of space missions.

To advance the field, this paper examines recent contributions and innovations aimed at addressing the challenges encountered during these critical phases of robotic operations. By exploring advancements in capture techniques, control strategies, the pre-capture and post-capture phases, and experimental validations, it highlights progress, identifies existing gaps, and proposes directions for future research. These efforts aim to enhance the capabilities and reliability of space robotic systems, paving the way for more effective on-orbit servicing (OOS) and space debris removal operations.

Understanding the historical milestones that have shaped the field of space robotics provides critical context for these advancements. Since the launch of the Shuttle Remote Manipulator System (SRMS) in 1981, space robotics for OOS have experienced substantial advancements and innovations. Significant space robotics initiatives for OOS have been conducted on space shuttles, as well as on both the interior and exterior of the International Space Station (ISS) and the China Space Station

(CSS), and on satellites. These pioneering efforts have been spearheaded by Canada, the United States, Germany, Japan, China, and other nations, as depicted in Fig. 1.

Among these advancements, the role of on-orbit robotic manipulators deployed by the ISS stands out as particularly significant. On-orbit robotic manipulators deployed by the ISS are integral for conducting complex external robotic tasks, playing critical roles in assembly, maintenance, and payload management aboard the station. These systems exemplify substantial advancements in aerospace technology and robotic engineering (Fig. 2).

The Canadarm2, officially known as the Mobile Servicing System (MSS), launched in 2001 aboard STS-100, significantly enhances the ISS's capabilities. This robotic arm can

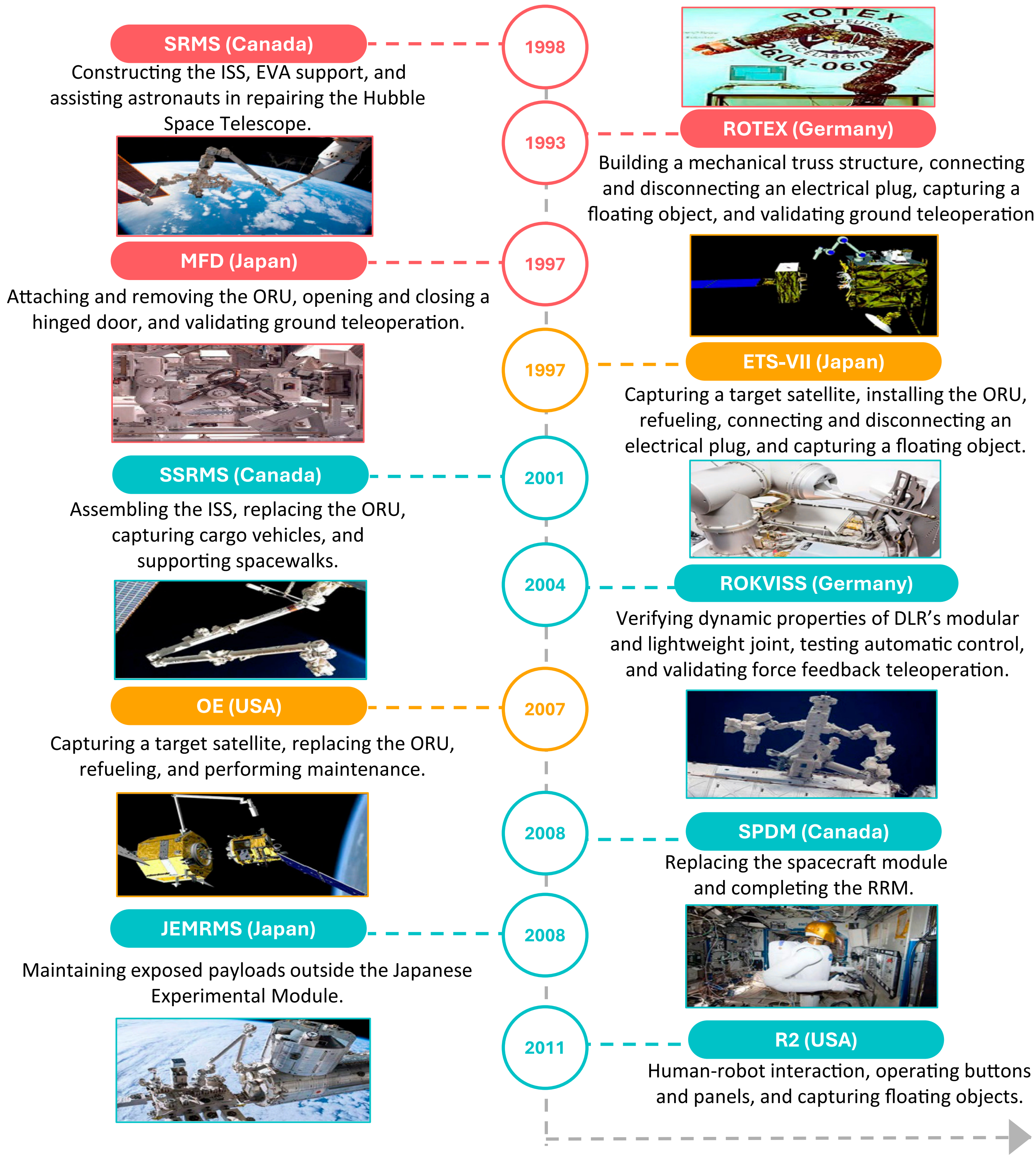

Fig. 1. Representative space robotic programs for OOS.

maneuver payloads up to 116,000 kg and is permanently mounted on the ISS, offering greater versatility compared to the original Canadarm used on the Space Shuttle [5]. Complementing Canadarm2, Dextre, also known as the Special Purpose Dexterous Manipulator (SPDM), is a smaller, dual-armed robot from Canada. It excels at performing tasks that

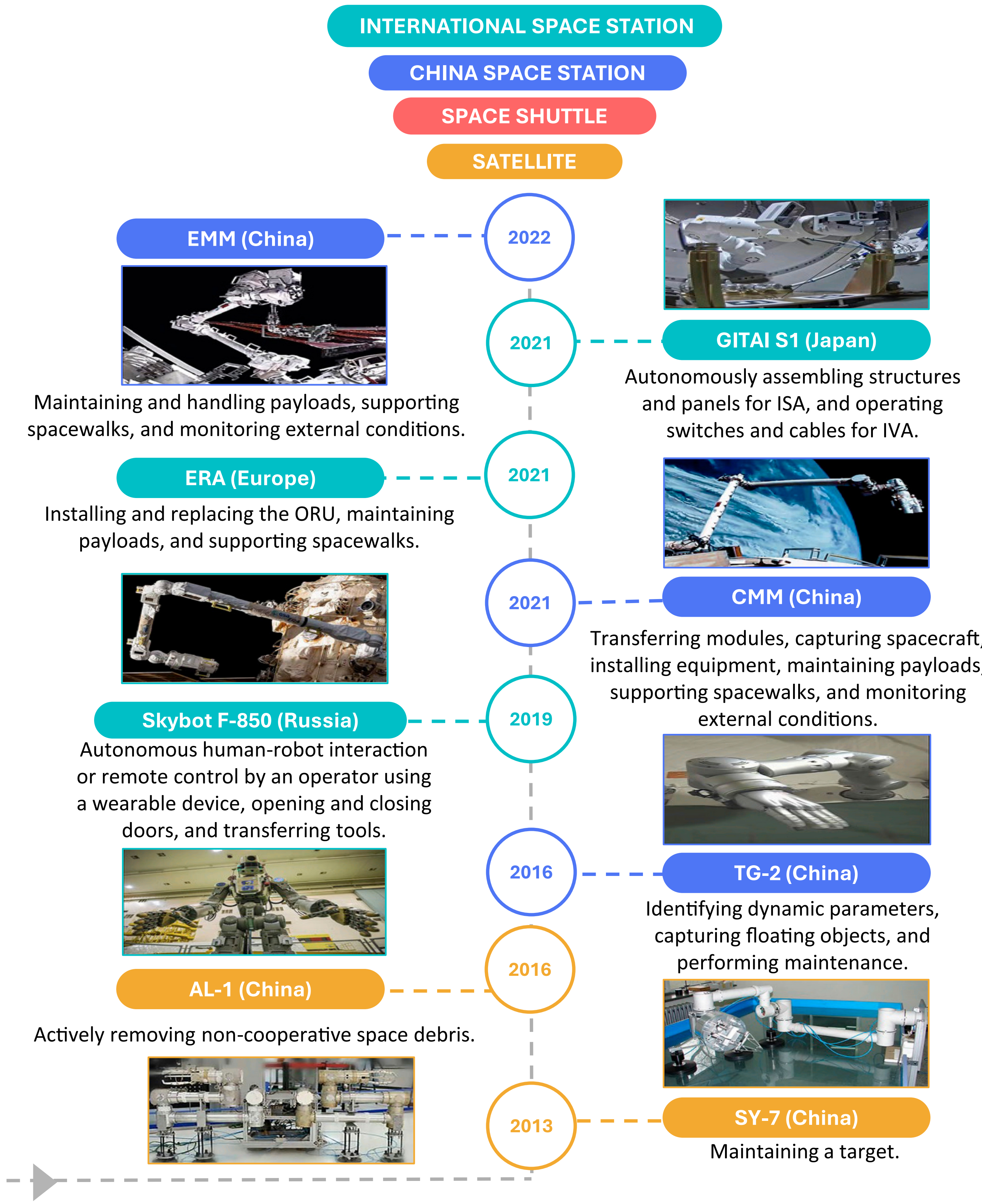

Fig. 1 (continued). Representative space robotic programs for OOS.

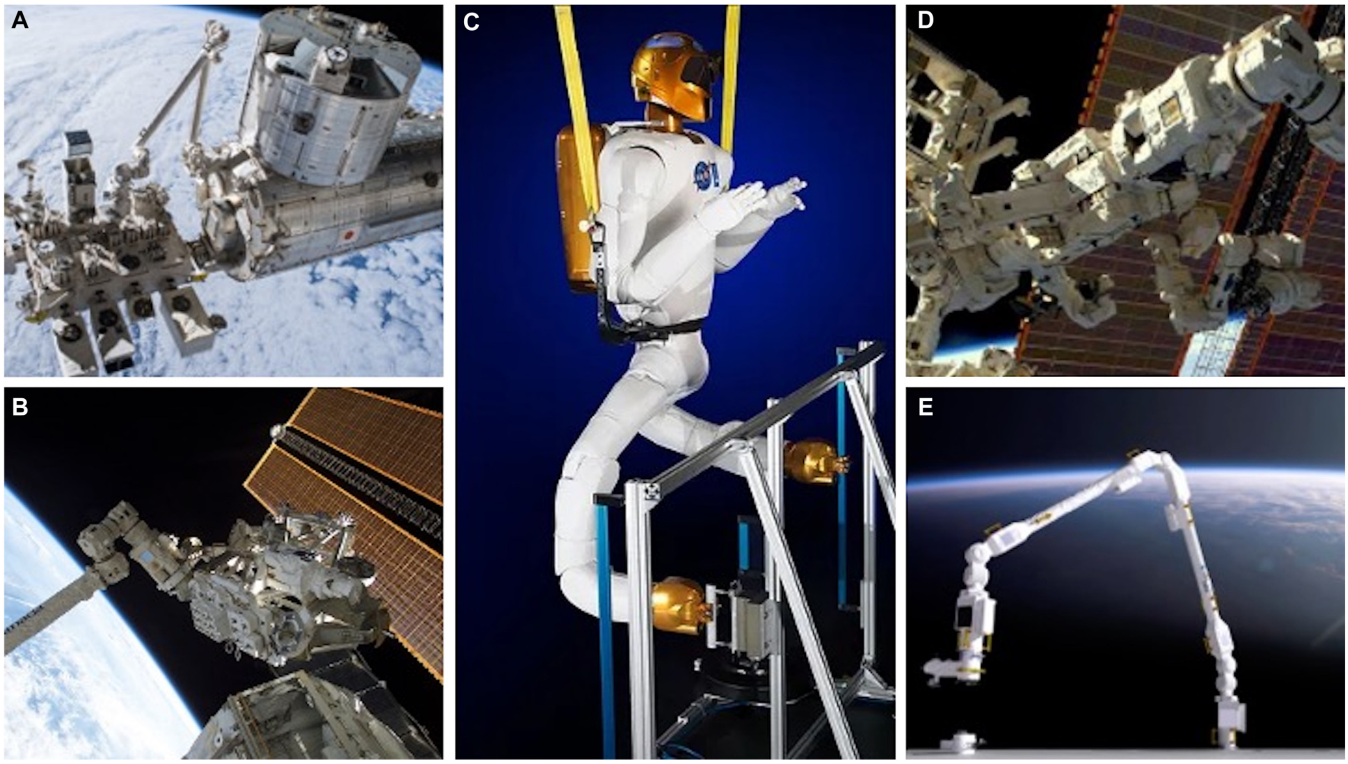

Fig. 2. A showcase of space robotics: Kibo (A) [9], Canadarm2 (B) [5], NASA's Robonaut2 (C) [66], SPDM/Dextre (D) [6], and the European Robotic Arm (E) [7].

are too delicate for the larger arms, such as handling intricate components and conducting complex assemblies. These operations, once necessitating risky spacewalks by astronauts, are now safely managed by Dextre, greatly enhancing both efficiency and safety aboard the ISS [6]. Another critical system, the European Robotic Arm (ERA), set to operate on the Russian segment of the ISS, extends the operational capabilities initially established by the Canadarm series. This 11-m-long arm, equipped with 2 end-effectors, enables it to "walk" across Russian modules, assisting in station assembly, docking, and payload maneuvers, reflecting European advancements in robotic technology [7].

In Japan, the Remote Manipulator System (JEM-RMS), also known as the Kibo Remote Manipulator System, is integrated within the Kibo Laboratory module. It features a main arm approximately 10 m long and a smaller arm crucial for managing experiments and smaller payloads, thus enhancing the ISS's functionality in scientific and technical endeavors [8]. Further adding to the robotic workforce, Robonaut 2, developed by the National Aeronautics and Space Administration (NASA), is a humanoid robot designed to assist astronauts with tasks too hazardous for humans. This robot, which can operate autonomously or in collaboration with crew members, showcases the potential of humanoid robotics in taking over dangerous tasks and improving safety aboard the ISS. Together, these robotic systems form a robust network that supports a wide range of operations, significantly extending human presence and capabilities in space [9].

As the field of OOS continues to evolve, the focus has expanded to developing innovative solutions for handling noncooperative targets and advancing orbital servicing missions. The targets captured during these missions are typically cooperative and equipped with relative navigation sensors and capturing interfaces. To advance practical orbital servicing missions in the 21st century, a new system concept has been developed for an orbital servicing vehicle named Hyper-OSV (Orbital Servicing Vehicle). Hyper-OSV features higher-speed manipulation capability and a larger operational area compared to the OSVs proposed in the 1990s. Its main innovation lies in separating the operational function from the long-term in-orbit survival functions, such as solar panels and a large communication antenna [10].

In respect to space debris removal with manipulators, there are currently no operational systems; however, many innovative procedures have been proposed by researchers to address this issue. One significant effort is the Deutsche Orbitales Servicing Mission (DEOS), Germany's OOS satellite concept. DEOS focuses on developing and evaluating procedures and techniques for the rendezvous, capture, and de-orbiting of an uncontrollable satellite from its operational orbit [11]. Similarly, E.deorbit was a pioneering mission that required new advancements, such as capturing uncooperative space debris with a spacecraft and then de-orbiting it, a feat that had never been accomplished before [12]. European Space Agency's (ESA) space servicing vehicle, which has evolved from the E.deorbit mission, is anticipated to launch by 2028, marking a significant step forward in the field of space debris management and orbital servicing.

Capture Techniques

The effective capture and manipulation techniques for OOS and space debris removal are crucial for tasks such as refueling, repairing, and repositioning satellites, as well as eliminating noncooperative targets. In this section, the recent OOS missions and space debris capturing techniques are discussed.

Effective Capture and Manipulation Techniques for OOS

Capture tools for space robots often adopt a gripper configuration, enabling the connection between the chaser and target satellites by closing the gripper's fingers around the target satellite. A variety of innovative mechanisms have been developed to effectively capture and manipulate objects in space, particularly for cooperative targets. A notable example is the work of Honeybee Robotics, which developed advanced grippers for space applications as part of the Defense Advanced Research Projects Agency (DARPA) Robotic Servicing of Geosynchronous Satellites (RSGS) program. Honeybee created 2 unique flight subsystems: the Universal Gripper Anchor (UGA), capable of grasping a variety of targets on the satellite to be serviced and providing an electromechanical mounting interface for modular nanosatellites, and the Satlet Grasper Tool (SGT), designed to secure and manipulate nanosatellite payloads using the servicing satellite's dexterous robotic arms [13].

DARPA has been at the forefront of robotic servicing advancements, starting with the Orbital Express program in 2007, which demonstrated the feasibility of robots refueling satellites and securing cooperative targets in space. Building on this foundation, the RSGS program has further developed robotic arms capable of repairing, upgrading, inspecting, and repositioning satellites, as shown in Fig. 3, which highlights the capabilities of DARPA's dexterous robotic arms in tasks such as high-resolution inspection, anomaly correction, cooperative relocation, and upgrade installation, paving the way for enhanced capabilities in space operations. Building on this foundation, the RSGS program has further developed robotic arms capable of repairing, upgrading, inspecting, and repositioning satellites, paving the way for enhanced capabilities in space operations [14].

The Chinese Space Station Manipulators (CSSM) consist of 2 robotic arms: the Core Module Manipulator (CMM), a larger 10.5-m arm, and the Experimental Module Manipulator (EMM), a smaller 5-m arm (Fig. 4). The CMM, with 7 joints, handles payloads up to 25,000 kg, reaching tip velocities of 0.3 m/s and angular velocities of 3°/s. Its symmetric design allows it to "walk" by relocating itself across the station. The EMM supports payloads up to 3,000 kg, with tip velocities of 0.2 m/s and angular velocities of 3°/s. It can operate from a fixed point or from the CMM, extending the combined reach to over 15 m. Both manipulators are equipped with force-motion control, operable in automated or remote modes, and are integrated with advanced systems like extended Kalman filters (EKF) and vision-based measurement for precision [15].

The CMM employs a cable-snared end-effector with a tendon-sheath transmission system. This mechanism provides passive compliance, allowing it to handle positional misalignments and enabling soft captures to minimize impact forces during payload engagement. The design is optimized for capturing large payloads, supporting station assembly and maintenance tasks.

The EMM features a 3-finger, 3-petal end-effector designed for precise operations. It utilizes active compliance control, supported by integrated force/torque sensors, to dynamically adjust grip forces. This enables it to securely handle delicate instruments, perform scientific experiments, and assist in tool operations with high precision.

Together, the CMM and EMM form a macro-micro system, where the larger arm provides broad coverage and heavy-lifting capabilities, while the smaller arm handles intricate, fine-detailed

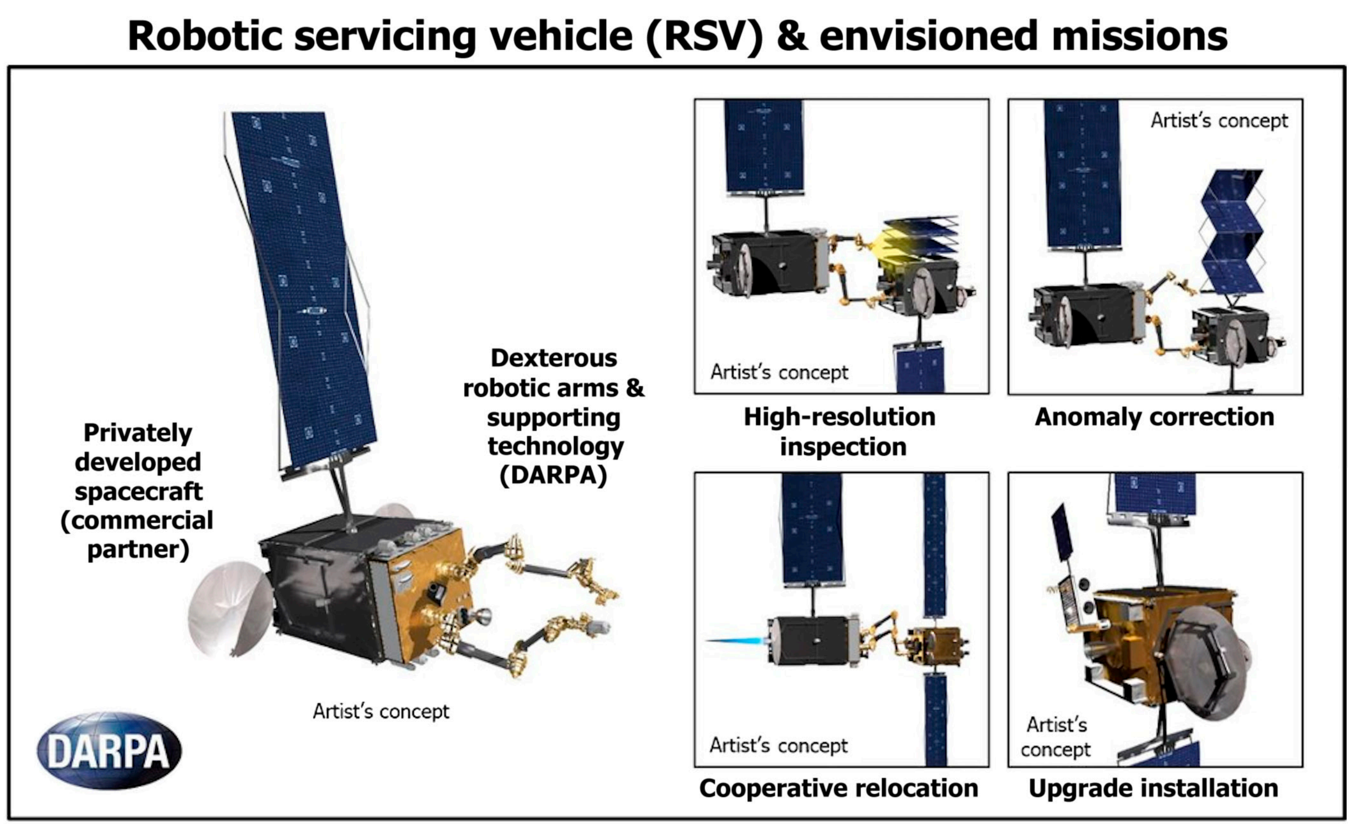

Fig. 3. DARPA Robotic Servicing of Geosynchronous Satellites (RSGS) [4].

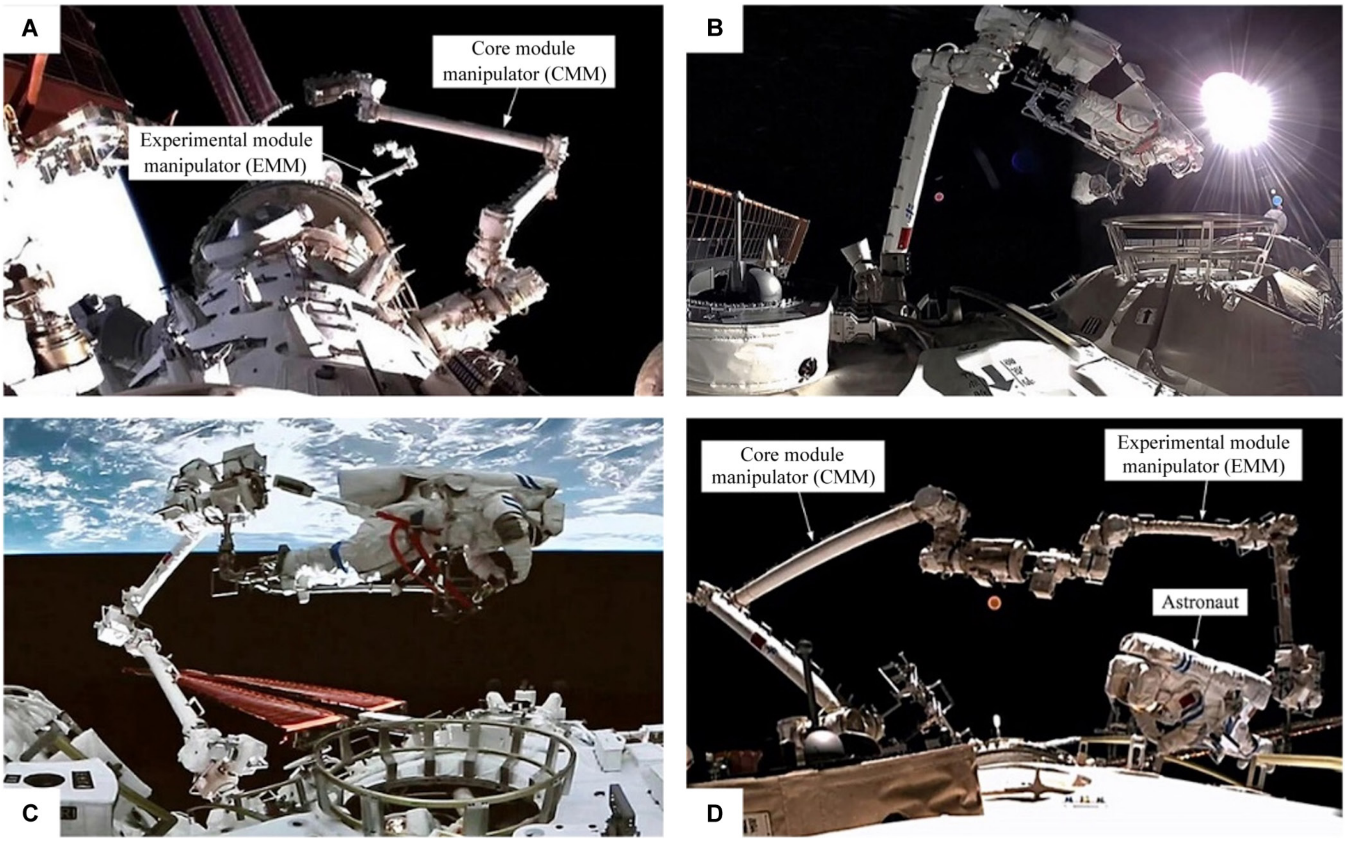

Fig. 4. CSSRMS and its components for OOS. (A) CSSRMS. Reproduced with permission. (B) CMM supporting EVA for an SZ-13 astronaut. Reproduced with permission. (C) EMM supporting EVA for an SZ-14 astronaut. (D) CMM and EMM cooperatively supporting EVA in series for an SZ-14 astronaut. Reproduced with permission [67].

tasks. This combination ensures versatile and robust operational capabilities for the Chinese Space Station [16].

The evolution of space robotic arms, from Canadarm1 to Canadarm2, demonstrates a progression in design and capabilities to meet the growing challenges of space exploration. Canadarm1 laid the groundwork with its innovative steel cable-snared mechanism, enabling reliable capture and manipulation of payloads during Space Shuttle missions. Canadarm2, a significant upgrade for the ISS, introduced advanced latching systems and integrated electrical connectivity, making it versatile enough to handle larger, more complex tasks. Table 1 compares these 2 milestones in space robotics, emphasizing their capturing techniques and end-effector designs [16].

Following Canadarm1 and Canadarm2, Canadarm3, developed by the Canadian Space Agency (CSA) in collaboration with MDA for NASA's Lunar Gateway, continues the legacy of Canadian innovation in space robotics. This next-generation robotic system, designed with advanced artificial intelligence (AI) for autonomous operations, will handle maintenance, repair, and inspection tasks, assist astronauts during spacewalks, and support research in lunar orbit and on the Moon's surface. Canadarm3 features an 8.5-m robotic arm, a smaller dexterous arm, and a tool caddy. The smaller arm is designed to transfer mission-critical materials and assist in repairs, significantly reducing the need for astronaut spacewalks. A key feature of Canadarm3 is its autonomous decision-making capability, crucial for long missions with communication delays. The system will be responsible for relocating modules, capturing spacecraft, and supporting extravehicular activities (EVAs) [17]. However, there is not much publicly detailed information currently available about Canadarm3's end-effector, although it is expected to incorporate advanced latching mechanisms and autonomous capabilities for precision and reliability in demanding lunar operations.

Effective Capture and Manipulation Techniques for Space Debris Removal

Space debris, which includes non-operational satellites, rocket upper stages, and residual fragments from explosions, poses unique challenges for space debris removal missions. Unlike OOS missions involving cooperative targets, space debris objects often provide no information to the chaser satellite and may exhibit tumbling motion, increasing the complexity of the task. In such missions, the end-effector plays a pivotal role in robotic arm operations. As the component directly involved in the capturing process and contact with the target, the end-effector's reliability and stability are critical to the mission's success [18].

For most targets, especially those lacking distinctive capture points, it is difficult for 2- or 3-finger end-effectors to meet mission requirements. To address this, researchers have focused on developing structurally advanced end-effectors. These designs enhance the capture error margin and reduce the need for high precision. Additionally, end-effectors with passive compliance offer significant advantages, such as preventing target escape, absorbing shocks, and minimizing chattering during the capture process.

Table 1. Comparison of capturing techniques and end-effector designs of Canadarm1 and Canadarm2

Aspect	Canadarm1	Canadarm2
Capturing mechanism	Steel cable-snared mechanism for soft capture and high misalignment tolerance.	Latching mechanism with 4 units for rigid mechanical and electrical connections.
End-effector size	Compact cylindrical design	Larger rectangular design.
Key subassemblies	Capture subassembly and rigidizing subassembly.	Capture, rigidizing, and latching and umbilical subassemblies.
Actuation	Dual-motor system (master and backup).	Single motor system with redundancy for latching units.
Misalignment tolerance	High tolerance for positional and angular misalignments, particularly for cooperative targets.	Lower positional misalignment tolerance but higher rigidity for larger payloads.
Payload compatibility	Suitable for smaller and simpler payloads.	Designed for larger payloads with higher mass and inertia.
Additional features	Focus on soft capture and misalignment tolerance.	Enhanced latching for precision docking and integrated electrical connections.

Various mechanisms have been designed to capture noncooperative targets, using innovative grippers and end-effectors to securely grasp and manipulate objects in space. Among these are 3 main types of end-effectors commonly used in active debris capture and removal tasks: reciprocally bonded, internally caged, and externally folded. Each of these designs addresses the unique challenges posed by space debris and contributes to achieving robust and effective debris removal. Reciprocally bonded structures rely on secure bonding mechanisms and are highly effective for targets without specific capture points. Internally caged structures use geometric constraints to secure targets and are designed to reduce positional error during capture. Externally folded systems, on the other hand, offer a larger capture range and allow for capturing targets with complex rotational dynamics [19].

Table 2 illustrates the pros and cons of each method, highlighting their strengths and limitations for different operational scenarios. Additionally, Table 3 provides a summary of notable works employing these methods, offering insights into how each approach has been applied in space debris removal research. These comprehensive comparisons help evaluate the suitability of each design for specific mission requirements,

Table 2. Advantages and disadvantages of reciprocally bonded, internally caged, and externally folded end-effector methods for space debris capture

Method	Pros	Cons
Reciprocally bonded	Independent of target size.	Instantaneous transmission of impact forces and moments.
	Simplifies the capture process.	Requires high structural strength to avoid fractures.
	Reliable for firm bonding.	
Internally caged	Low accuracy requirements for position and orientation.	Limited by the maximum size of debris it can handle.
	Secure capture post-engagement.	High risk of debris escape during pre-capture.
	Absorbs shocks and minimizes chattering.	Risk of unforeseen collisions.
	Flexible designs (multi-loop, bionic).	Requires extensive ground testing for feasibility.
Externally folded	Larger capture range compared to other methods.	Requires prior knowledge of the target's physical model.
	Cushioned structures reduce impact forces.	Dynamic coupling delays capture until fully expanded.
	Allows rotation of the target on a specific axis.	Research still needed for motion decoupling and reliability improvements.
	Flexible design options (closed and envelope configurations).	Increased design complexity and cost.

Table 3. Summary of notable works employing reciprocally bonded, internally caged, and externally folded methods for space debris capture

Authors	Capturing method category	Description
Matsushita and Yoshida [72]	Internally caged	Demonstrated a U-shaped end-effector for dual-arm robots using geometric constraints to capture non-axisymmetric objects like cubes and rectangular prisms.
Zhang et al. [73]	Internally caged	Explored geometric cage pairs for dual-arm space robots; further ground experiments are needed to validate this approach.
Sun et al. [74]	Externally folded (caging)	Developed a capture mechanism for the launch adapter ring (LAR) with a step-by-step process to secure and rigidify the target. Successfully validated for real-world scenarios.
Zhang et al. [75]	Reciprocally bonded	Proposed adhesive arms for debris capture, modeled using multibody dynamics and the absolute nodal coordinate formulation (ANCF) (Fig. 5A).
Hawkes et al. [76]	Reciprocally bonded	Described a 3D surface grasping mechanism utilizing dry adhesion, inspired by geckos, for secure bonding to debris surfaces.
Yang et al. [68]	Internally caged	Introduced a flexible, sea-anemone-inspired mechanism with continuum arms that envelop and lock onto targets of varying sizes (Fig. 5B).
Li et al. [77]	Externally folded (caging)	Focused on externally folded end-effectors with constant-torque hinges for compact storage and grippers that create a stable caging effect. Included dampers for detumbling and slip rings for signal transmission (Fig. 5C).

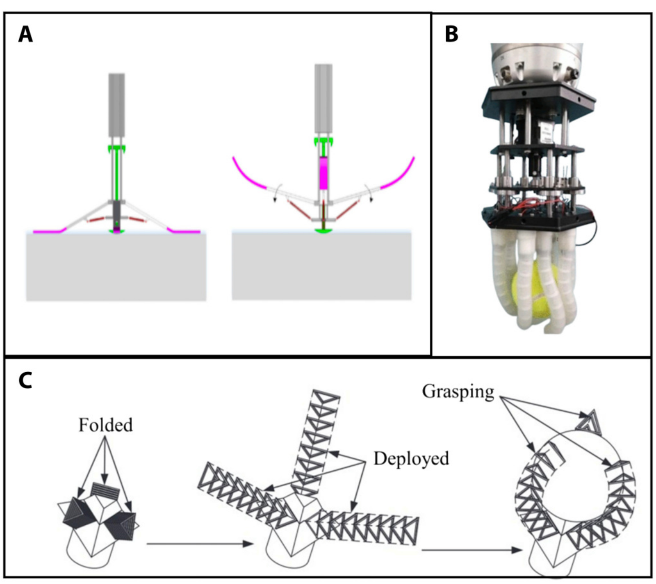

Fig. 5. Robotic gripper designed for capturing and manipulating space debris [19]. (A) Reciprocally bonded end-effector. (B) Internally caged end-effector [68]. (C) Externally folded end-effector.

paving the way for more advanced and reliable debris removal systems.

Control Strategies

The successful operation of space robots relies on the development and implementation of advanced control strategies tailored to their specific classifications and mission objectives. Each category of space robots—whether free-flying or free-floating—presents unique challenges that demand specialized control approaches to achieve precision, stability, and efficiency in task execution. This section summarizes some of the control strategies that have been utilized in recent studies.

Free-Flying Space Robots

Free-flying space robots rely on thrusters or reaction wheels to maneuver independently, offering 6 degrees of freedom (6-DOF) for enhanced mobility and autonomy. While these capabilities significantly improve their versatility, they also introduce challenges such as the need for precise collision avoidance, high fuel consumption, and increased system complexity and maintenance requirements [20].

To address these challenges, researchers have proposed various control schemes for managing free-flying space manipulators. Among these, adaptive control schemes have been specifically developed for trajectory tracking and attitude control of free-flying space systems. These approaches aim to tackle issues such as uncertainties in system dynamics, external disturbances, and energy efficiency constraints.

One notable example is the modified adaptive sliding mode-based control strategy proposed by Han et al. [21,22], which effectively manages uncertainties in system dynamics and external disturbances. This robustness is particularly crucial in space applications, where precise system modeling is inherently challenging. The method ensures stable tracking of desired trajectories, which is essential for complex tasks such as capturing and detumbling noncooperative targets. In free-flying systems, this control strategy plays an even more vital role by actively managing base dynamics to provide stable support for the manipulator's operations. Additionally, Han et al. [21] described the design of an elastic hemispherical claw to reduce collision impacts during debris capture. Ground experiments validated the contact dynamics and capture ability of this claw, confirming its effectiveness in minimizing impact forces and enhancing stability.

Adaptive controllers have also been utilized for attitude control in spacecraft handling large loads with unknown dynamic properties. For instance, Shi et al. [23] developed a direct adaptive controller that satisfies the almost strictly passivity conditions required for guaranteeing the asymptotic stability of the closed-loop nonlinear adaptive control system. Simulation results for a rigid-body, large rest-to-rest maneuver demonstrated robust attitude control behavior, with performance unaffected by large uncertainties in the principal moments of inertia. This directly addresses the critical challenge of maintaining precision and stability during operations. Furthermore, testing the adaptive control law on MDA's Space Station Portable Operations Training Simulator for an ISS free-flyer robotic capture scenario showed that the adaptive algorithm improved attitude hold performance compared to the ISS proportional-integral-derivative (PID)-based attitude controller, all without requiring additional energy demand.

Another proposed approach for free-flying space robots is the geometric control strategy demonstrated by Xu et al. [24]. This method achieves position and attitude tracking control with predefined-time convergence, enabling the spacecraft and end-effector to concurrently track their reference trajectories within a predefined time. Illustrative simulation results highlight the rapid and stable tracking control performance, emphasizing the effectiveness of this approach.

Additionally, Shibabw and Tamiru [25] explored a fuzzy sliding mode controller (FSMC) for trajectory tracking control of a space robot manipulator in joint space while assessing its robustness. Simulations in MATLAB/Simulink under external disturbance and parametric variation conditions showed that FSMC is robust, provides excellent trajectory tracking performance, reduces the integral time absolute error (ITAE), and eliminates the chattering effect observed in conventional sliding mode controllers (SMCs). Comparative analysis further demonstrated that FSMC achieved lower ITAE than SMC, showcasing its superior performance.

Finally, Mohamed et al. [26] proposed a control algorithm that combines feed-forward compensation to eliminate dynamic coupling between the base spacecraft and the manipulator, decoupling the system for independent control. This approach is followed by feed-forward linearization, allowing the application of linear controllers such as linear quadratic regulator (LQR) and PID. Mohamed's method addresses challenges like trajectory tracking under extreme perturbations, noise, and parametric uncertainties. Simulation results revealed that the LQR controller provided higher trajectory tracking accuracy and robustness, whereas the PID controller offered greater fuel efficiency, making the choice of controller dependent on specific mission requirements.

While not exhaustive, these examples highlight the variety of control strategies developed to address the unique challenges of free-flying space robots, reflecting the ongoing innovation and adaptation in this field.

Free-Floating Space Robots

Free-floating space manipulators (FFSMs) operate with an uncontrolled base, allowing it to drift in response to arm movements [27]. These robots rely on momentum conservation, making them particularly suitable for tasks such as maintenance, assembly, and scientific experiments in space where base stabilization is not required.

To address the challenges associated with FFSMs—such as trajectory tracking, managing the dynamic coupling between the manipulator and the base, and handling parameter perturbations—researchers have developed a variety of advanced control strategies. These innovative approaches focus on ensuring precise manipulator control while accounting for the effects of the drifting base, offering robust solutions for managing the complexities of FFSM dynamics.

One such approach was presented by Guo et al. [28], who proposed an improved nonlinear model predictive control (NMPC) method that integrates the concept of sliding mode variable structure. This enhancement ensures greater robustness compared to conventional NMPC methods, making it better suited for managing uncertainties and disturbances in space environments. Theoretical analysis highlights its effectiveness, and this novel dynamic modeling and control strategy has shown significant potential for OOS tasks involving free-floating dual-arm space robots. By addressing the complexities of multi-DOF space systems, this method offers valuable insights and advancements in the field of space robotics.

Building on this, another innovative control strategy was presented in Ref. [29], involving repetitive learning sliding mode stabilization combined with an optimal controller. This method effectively suppresses elastic vibrations in the base, joints, and links of the system while achieving stable tracking of the desired signal with a single control input in under 10 s. Such rapid stabilization demonstrates its practicality and effectiveness in real-time space operations.

Despite the advancements in these control strategies, conventional controllers remain limited in addressing the coupled dynamics of nonlinear systems, especially as the robot's DOFs increase. The modeling and implementation of sophisticated control strategies become increasingly complex as system complexity grows. To overcome these limitations, model-free deep reinforcement learning (RL) has emerged as a promising alternative. RL eliminates the need for precise dynamic modeling by learning complex control policies directly from interactions. It has demonstrated exceptional success in robotic manipulation, offering a robust solution for handling the intricate dynamics of FFSMs and effectively managing external disturbances.

More cases where these control strategies have been applied are summarized in Table 4, providing a comprehensive overview of the diverse approaches used in addressing the challenges of free-floating space robots. Collectively, these strategies highlight the innovative and versatile solutions developed to enhance the efficiency and robustness of space robotics.

Pre-Capture Phase

During the observation and planning stage, the objectives include obtaining the target's 6-DOF motion data, which encompass its position, orientation, and both linear and angular velocities. Identifying the target's inertia parameters and other physical characteristics is also crucial. This stage involves determining the optimal timing and location for capture, planning the trajectory for the final approach and engagement, and ensuring precise motion control of the system. For a malfunctioning satellite or space debris exhibiting unpredictable

Table 4. Overview of control methods for free-floating space robots: This table categorizes key studies on the development and application of various control strategies for free-floating space robotic systems

Category	Authors	Key contributions
Reinforcement learning-based methods	Al Ali et al. [27]	Developed a path planning method using deep deterministic policy gradient (DDPG) for 6-DOF FFSM.
	Beigomi and Zhu [34]	Used reinforcement learning for robotic pre-grasping in microgravity, bridging the sim-to-real gap for robotic grippers.
	Srivastava et al. [35]	Proposed a model-free control method using proximal policy optimization (PPO) for 9-DOF control of rotation floating space robots.
	Cao et al. [78]	Introduced the EfficientLPT algorithm, using reinforcement learning with prior policy guidance to improve path tracking for spinning targets.
	Li et al. [79]	Presented a DRL-based constrained motion planning method for dual-arm FFSM, addressing self-collision avoidance and velocity constraints.
Model predictive control (MPC) methods	Guo et al. [28]	Developed improved nonlinear model predictive control, combining NMPC with sliding mode control for dual-arm FFSM stability.
	Psomiadis and Papadopoulos [80]	Proposed a model-based MPC design to handle uncertainties and disturbances in FFSM systems, outperforming MB/PID controllers.
	Rybus et al. [81]	Implemented an MPC-based trajectory control for satellite manipulators, compensating for uncertainties and disturbances.
Robust control method	Shang et al. [82]	Applied fractional-order sliding mode control to improve accuracy and manage uncertainties in FFSM.
	Dou and Yue [83]	Proposed a fractional-order sliding mode control with a disturbance observer for trajectory tracking under uncertainties.
	Xie and Yu [84]	Developed a backstepping-based sliding mode controller with a state observer for FFSM with flexible joints and actuator failures.
	Yan et al. [85]	Presented a fixed-time trajectory planning combined with nonsingular terminal sliding mode control to improve accuracy and disturbance handling.
	Fu et al. [29]	Developed a repetitive learning sliding mode control for stabilization during satellite capture, using singular perturbation theory.
Classic control methods	Vyas et al. [86]	Proposed a quaternion-based approach combined with LQR for multi-body FFSM control in zero-gravity.
Adaptive control methods	Xie et al. [87]	Developed an RL-based adaptive small chattering sliding mode control using time-delay estimation for FFSM with uncertainties.

motion, accurately predicting its motion pattern and assessing its kinematic and dynamic properties are essential. Additionally, guiding a robotic manipulator to execute a close-range rendezvous with the target satellite, while maintaining robust motion control, is a key task in robotic orbital servicing missions [30].

Motion Planning Techniques

Motion planning in space presents unique challenges due to the microgravity environment, unmodeled surroundings, and computational constraints inherent to spacecraft systems. Unlike Earth, where gravity serves as a constant reference for orientation and motion, the near weightlessness of space requires alternative methods to determine orientation and plan trajectories. The absence of gravity and frictional forces profoundly impacts how robots move and stabilize, necessitating planners to incorporate these dynamics into trajectory design. Additionally, the space environment is vast and unpredictable, with hazards such as asteroids, debris, and unmapped regions posing significant risks. Robust planning algorithms must adapt to unforeseen obstacles and operate effectively with limited environmental data, dynamically adjusting to new information as it becomes available. Compounding these difficulties, onboard spacecraft computers have constrained processing power compared to terrestrial systems [1]. This limitation demands the development of computationally efficient algorithms capable of real-time performance, ensuring reliable and adaptive guidance despite restricted resources. In this section, works proposed to overcome these challenges are reviewed, highlighting advancements aimed at addressing the unique demands of motion planning in the dynamic and unforgiving environment of space.

Motion planning, encompassing both trajectory planning and path planning, serves as the foundation for efficient robot operation. Trajectory planning forms the foundation for controlling the motion of a robotic arm and plays a crucial role in determining the quality of the completed operation. As a prerequisite for trajectory tracking control, effective trajectory planning directly influences the accuracy of the robot's trajectory tracking. It also ensures the generation of feasible, collision-free sequences of positions and timings, which are essential for safe and efficient operation. Furthermore, its performance affects key factors such as motion efficiency, smoothness of movements, and energy consumption.

In this context, Rybus et al. [31] proposed a bidirectional rapidly exploring random tree (RRT) algorithm that plans collision-free manipulator trajectories while adjusting satellite orientation, showing improvements over basic RRT methods. An enhanced BiRRT algorithm with pseudo-velocities further improves computational efficiency and accuracy [31]. Wang et al. [32] explored the application of the particle swarm optimization (PSO) strategy for trajectory planning of kinematically redundant space robots operating in free-floating mode. The dynamic singularities encountered during path-dependent movements significantly limit the robot's available workspace and often require excessive joint velocities to navigate through such singular configurations. To address these challenges, Wang et al. employed direct kinematics equations combined with PSO for trajectory planning. However, it is important to note that these methods are primarily designed for trajectory planning tasks with fixed initial and final points.

As previously mentioned, the complex dynamic modeling of multi-degree-of-freedom (DOF) manipulators, particularly for space robots with dual arms, presents a significant challenge. As a result, trajectory planning is often performed offline and then tracked in real time. However, this approach becomes inadequate when the target object moves relative to the servicing space robot. To overcome this limitation, a model-free RL strategy has been proposed, enabling the training of policies for online trajectory planning without relying on the dynamic or kinematic models of the space robot [33].

While some studies have explored single-target trajectory planning for space robots using RL techniques [27,34,35], these methods often fail when the target position changes. Moreover, they are generally unsuitable for tasks requiring the end-effector to follow a specific trajectory. To meet the demands of space missions, it is essential to develop multi-target trajectory planning strategies that operate within a large initial configuration space. However, the dynamic nature of target positions during training introduces significant challenges in optimizing strategies for multi-target tasks, often resulting in reduced precision compared to single-target scenarios. Furthermore, existing research has not adequately tested the robustness of trained strategies under diverse and realistic conditions, which is an essential requirement for operating in the complex and unpredictable space environment. Thus, the primary challenge in multi-target trajectory planning lies in achieving high precision without compromising robustness, particularly when dealing with expansive initial configuration spaces.

To address these challenges, Wang et al. [36] proposed a multi-target trajectory planning strategy for a 6-DOF free-floating space robot, optimized using the proximal policy optimization (PPO) algorithm. To further enhance the PPO algorithm, augmentation techniques were incorporated, significantly improving its precision and stability in reaching multiple targets. This approach presents a promising solution to the challenges associated with multi-target tasks in dynamic space environments.

Path planning, unlike trajectory planning, generates a sequence of configurations (or waypoints) that the robot should pass through, focusing solely on the spatial aspect of the motion. In scenarios where the robot is approaching a target, an online path planning mechanism is necessary to modify the end-effector trajectory in real time based on updated target motion predictions. This ensures precise and adaptive motion as the robot responds to dynamic changes in the target's position and movement [37].

Hirano et al. [38] presented a simplified online path planning method that incorporates constraints to ensure that the end-effector reaches the predicted grasping location simultaneously with the moving grasping point and at the same velocity. This approach enables the robot to automatically update the reference end-effector trajectory in real time, adapting to the dynamically changing states of both the robot and the target during the approach. This ensures precise and adaptive motion, allowing the robot to effectively interact with moving targets. Additionally, Al Ali et al. [27] investigated path planning for 6-DOF free-floating space robotic manipulators using a deep deterministic policy gradient (DDPG)-based RL approach. The method ensures that the end-effector's pose aligns precisely with the target while avoiding collisions with both the target and the manipulator's other links. It also smooths the manipulator's joint velocities, accounts for significant variations in the mass ratio between the manipulator and the base spacecraft, and enhances the robustness of path planning under noisy state observations. The findings highlight the capability of RL algorithms for real-world mission design, where noise in observations is inevitable.

Table 5 provides an overview of recent research trends focused on motion planning strategies aimed at addressing key challenges in the field to enhance the efficiency, precision, and safety of space robot motion planning.

Vision-Based Techniques

Vision-based estimation refers to the process of using visual data, typically acquired from cameras or other optical sensors,

Table 5. Summary of planning approaches in space robotics

Study/author(s)	Research focus	Key contributions
Tavana et al. [88]	Optimization-based collision avoidance for autonomous on-orbit assembly.	Proposed a novel technique using convex optimization to model collision avoidance constraints, integrating them into optimal control problems to generate nonconservative, collision-free trajectories in tight environments.
Zhang et al. [89]	Informed Bi-Quick RRT* algorithm for rational motion planning of 2-arm cooperative systems under multiple constraints.	Enhanced Quick-RRT* algorithm with a 2-tree concept and multi-objective bias expansion. Reduces computation time by 70% and path nodes by 40%. Effective in simulations with obstacle avoidance and directional constraints.
Faghihi et al. [90]	Kinodynamic inspection path planning for space structures in deep space environments.	Presented the random kinodynamic inspection tree algorithm, integrating coverage path planning with kinodynamic planning in 3D space. Extended RRT* with a new coverage strategy to satisfy full coverage. Simulations validated its performance for convex and concave shapes, generating smooth, collision-free, and continuous trajectories.
Basmadji et al. [91]	Motion planning of dual-arm space robot manipulators considering nonconserved linear and angular momenta.	New method for planning motion under external forces and moments without additional controllers. Calculates changes in momenta in the equations of motion. Verified by numerical simulations.
Zhang and Liu [92]	Motion planning strategy integrating optimization of spacecraft base's berth position for capturing floating targets with a space robot.	Unified motion planning framework using forward kinematics and parameter optimization. The "Grasping area" concept simplifies motion planning. Effective in 2D and 3D simulations.
James et al. [93]	Reactionless maneuvers for space robots during the pre-capture phase.	Utilizes reaction null space (RNS) and coordinate partitioning for planning trajectories that minimize attitude disturbances.

to estimate key parameters or states of a system. These states may include the position, orientation, velocity, or even physical attributes of a target. Cameras are rapidly becoming the preferred sensors for autonomous rendezvous alongside light detection and ranging (LiDAR) sensors, enabling pose estimation and motion tracking [1]. This shift is largely attributed to the development of compact and lightweight passive optical sensors, which serve as viable onboard instruments.

One of the methods within vision-based estimation and control is visual servoing. Visual servoing is a control technique in robotics that uses feedback from visual sensors to dynamically guide a robot's motion. A widely studied approach in visual servoing is the eye-in-hand configuration, where a camera is mounted on the manipulator's end-effector to monitor the motion of the target. This configuration provides a highly accurate and localized view of the target, with control accuracy improving as the camera moves closer to the target. However, a key limitation is that the target can move out of the camera's field of view, potentially leading to an undesired termination of the capture operation [39]. To address this issue, Kalman filters (KFs) have been proposed in the literature.

Larouche and Zhu [39] introduced a dual KF approach for the eye-in-hand position-based visual servoing (PBVS) control strategy, enabling the capture of a passively noncooperative target. This method enhances the robustness of the visual servo system and mitigates the time delay problem in PBVS by predicting the rendezvous point for capture.

Similarly, Mishra and Schmidt [40] developed an estimation scheme for vision-based target capture using an end-effector-mounted camera (eye-in-hand). Their approach incorporates a novel EKF to robustly estimate states and parameters based on available measurements, such as the relative pose between the target and camera, and the robot's kinematics. The proposed estimator demonstrates resilience to challenges commonly associated with vision sensors, ensuring reliable performance in vision-based operations.

Dong and Zhu [41,42] proposed a predictive visual servo kinematic control scheme for a robotic manipulator with an eye-in-hand configuration, aimed at autonomously capturing a noncooperative space target with unknown motion. The target's unknown motion is estimated using an integrated algorithm that combines photogrammetry and an adaptive extended Kalman filter (AEKF). The eye-in-hand configuration enhances the accuracy of motion estimation as the manipulator approaches the target, ensuring precise and reliable operation during the capture process.

Another visual-based estimation method leverages deep learning (DL) techniques, which have demonstrated significant potential in space missions. Despite their promise, this approach faces several notable challenges. Planets and stars often serve as background distractors for navigation systems, complicating the task of distinguishing the target. Additionally, the absence of an atmosphere and light diffusion in space creates difficult visual conditions. Strong shadows and highly variable illumination can lead to extreme image contrasts and a low signal-to-noise ratio, further impairing performance.

Moreover, there is a scarcity of training datasets for noncooperative navigation of spaceborne objects, making it challenging to effectively train DL models. Concerns about the reliability of DL techniques also limit their adoption in the space industry, where robust and dependable systems are critical for mission success. To tackle these challenges, various studies have proposed innovative solutions.

Sonawani et al. [43] proposed the use of a convolutional neural network (CNN) to uniquely determine the translation and rotation of an object of interest relative to the camera. The primary motivation for employing a CNN model is to support object tracking in space assembly tasks, where traditional feature-based methods may not always be sufficient. A significant advantage of CNN models over feature-based approaches is their adaptability. CNNs can be tailored to track different objects simply by training the model on a sufficiently large dataset that includes the new object, making them a versatile solution for a wide range of applications.

Cassinis introduced an adaptive CNN-based unscented Kalman filter (UKF) for pose estimation of uncooperative spacecraft. To enhance the performance of the CNN on realistic space imagery, a novel data augmentation scheme was employed, leveraging light randomization to simulate varied illumination conditions commonly encountered in space environments. This approach improves the robustness and accuracy of pose estimation under challenging visual conditions.

Guthrie et al. [44] proposed an autonomous, real-time method for estimating the attitude of an unknown and uncooperative target spacecraft using DL technologies. The approach demonstrated high accuracy and robustness, achieving reliable results when used with LiDAR or RGB-D (red, green, blue—depth) sensors, which provide valuable depth information. While the method is also applicable to monocular cameras, its accuracy is significantly affected by the absence of depth data. Consequently, further refinement of the model is needed to achieve comparable performance when operating under this constraint.

More studies that have employed innovative visual methods are mentioned in Table 6, which summarizes how these methods enhance the capabilities of space robots in the pre-capture phase.

Post-Capture Phase

The post-capture phase is a critical and complex stage in space robotic operations, where the stability, safety, and success of the mission depend on effective handling of the captured object. During this phase, the primary objectives are to stabilize the target, manage system dynamics, and prepare the object for subsequent operations such as manipulation, servicing, relocation, or controlled deorbiting. Jankovic et al. [45] classified the attitude states of space objects into 2 categories: stable and tumbling. The tumbling category is further subdivided into fast, medium, and slow regimes based on angular velocity. Manipulator-based methods have proven effective for stabilizing objects with moderate rotational velocities. This classification provides a framework for understanding the challenges associated with targets, which can include tumbling noncooperative debris with unknown geometric and inertial properties or malfunctioning satellites lacking attitude or orbit control. These uncertainties make the post-capture phase inherently risky and demand advanced control strategies [46].

To address the challenges of stabilizing satellites in space, researchers have developed both model-based and model-free control strategies. For instances where a satellite's attitude experiences sudden changes, particularly during the capture of noncooperative targets transitioning to an unknown state, Ma et al. [47] proposed an RL-based method for re-stabilization. This adaptive control approach leverages deep RL to effectively manage satellite attitude control under such complex conditions. Their results demonstrate that this method can successfully restore satellite stability even when the motion and mass state are unknown, a scenario where traditional controllers often fail due to their dependence on precise mass parameter estimation.

On the other hand, Vyas et al. [48] introduced a model-based approach using a time-varying linear quadratic regulator (TVLQR) for stabilization along the detumbling trajectory. Their work presents significant contributions, including the development of a quaternion-based linearization method for multibody systems with a free-floating base and the application of TVLQR to stabilize the optimal detumbling trajectory. This highlights an alternative yet equally effective strategy within the domain of model-based control for space robotics.

In other study, Huang et al. [49] proposed a dynamic surface method that incorporates a robust dynamic control allocation strategy for the attitude control of a combined chaser-target system. The approach includes a disturbance observer-based dynamic surface control method, which demonstrates robustness against external disturbances and modeling errors in the reconstructed dynamics. Moreover, this control strategy enables the performance to be prescribed a priori and effectively avoids the "explosion of complexity" typically associated with backstepping methods.

Expanding on robust control methodologies, Beigomi and Zhu [34] tackled the attitude control problem of a combined spacecraft operating under inertial uncertainty. The study formulated the attitude dynamics of the system and introduced a composite adaptive finite-time controller based on constructive time-varying sliding manifolds. This robust control approach significantly enhances system resilience against uncertainties, although it illustrates the trade-off inherent in sliding mode control and its variations: Increased robustness can sometimes come at the expense of control accuracy.

To summarize the diverse control strategies employed during the post-capture phase of space robot manipulator systems, researchers have utilized a variety of approaches, each with distinct strengths and limitations. Model-based control methods are effective but often require precise parameter identification of the target, presenting significant challenges in uncertain conditions. Moreover, they depend on having an accurate dynamic model of the combined spacecraft, which is frequently impractical in real mission scenarios. Consequently, recent research has shifted focus toward auxiliary aspects of control systems, such as offline calibration, enhanced robustness,

Table 6. Summary of recent studies on visual techniques for pre-capture phases in space robotics

Study/author(s)	Visual techniques used	Pre-capture phase details
Li et al. [94]	Adaptive visual servoing, state observer.	Dual subsystem approach with adaptive visual servoing for feature point management and state observer for vibration suppression.
Tang et al. [95]	Visual data, LiDAR.	Capturing point cloud data via LiDAR before and after collision, estimating real-time position of debris' center of mass, identifying normalized dynamic parameters before collision.
Aghili [96]	ICP image registration, noise-adaptive Kalman filter, path planner.	Combines ICP for image registration, Kalman filter for dynamic estimation, fault detection, and optimal path planning, ensuring continuous operation under failure conditions.
Al-Shanoon and Lang [97]	3-D visual servoing, deep learning.	Combines 3D visual processing with neural networks for precise and adaptive handling of objects, enhancing accuracy and efficiency of robotic manipulators.
Ribeiro et al. [98]	Visual servo control, grasp detection using CNN.	Real-time processing of visual data to identify optimal grasp points and ensure object remains within the robot's field of view.
Kobayashi et al. [99]	Stereo image processing, 3DCG experiments.	Details an image processing algorithm for space debris removal using a microrobotic satellite. Enhances stereo camera system to identify and process circular components of debris under varying lighting conditions, accurately estimating the position and attitude of debris.
Luo et al. [100]	Image-based visual servoing, natural features.	Utilizes natural features from target images for visual servoing.
Dong and Zhu [101]	Photogrammetry, adaptive extended Kalman filter.	Integrates photogrammetry and an adaptive extended Kalman filter for real-time estimation of target's position and velocity, facilitating dynamic prediction of interception point.
Mishra et al. [102]	Nonlinear observer.	Estimates the inertial pose and the velocity of a free-floating noncooperative target using only relative pose measurements.
Christidi-Loumpasefski and Papadopoulos [103]	Visual and force sensors.	Determines inertial parameters of space objects using data from visual and force sensors, applying an impulse via a rod and measuring the response to infer parameters.
Lampariello et al. [104]	Visual servoing, extended Kalman filter.	Visual servo tracks reference trajectory, joint-space controller manages rigidization after grasping, using extended Kalman filter for robustness and predictions.
Larouche and Zhu [105]	Visual servoing, Kalman filter.	Dual Kalman filter for enhancing target tracking and pose estimation in visual servoing. Transitional decision-making guides through acquisition, approach, alignment, and capture phases.
Tzschichholz et al. [106]	3D-imaging with PMD camera.	Uses PMD camera for motion detection and prediction in near-range operations, leveraging rotation- and scale-invariant features, validated through simulations and experiments.

Table 7. Overview of control methods for space robots in post-capture operations

Authors	Control method	Purpose of the control method	Summary
Chen et al. [107]	Sliding mode control (SMC) and adaptive sliding mode control (ASMC).	Stabilization of an asymmetric system under disturbances and uncertainties.	Proposed a sliding mode controller for partial stabilization against external disturbances. An adaptive sliding mode controller with compensation laws was developed to address measurement inaccuracies in the inertia tensor and mass centroid, ensuring robust control.
Zhang et al. [108]	Adaptive integral sliding mode control (AISMC) with time-delay estimation (TDE).	Stabilization of a space manipulator after capturing noncooperative large-scale debris.	The system estimates coupling terms and lumped uncertainties using TDE, eliminating the need for prior knowledge. Adaptive sliding mode control compensates for TDE errors, while a PID-type integral sliding mode surface minimizes steady-state errors.
Nguyen-Huynh and Sharf [109]	Adaptive reactionless control and momentum-based estimation.	Minimizing base disturbances and identifying unknown inertia parameters post-capture.	Proposed an adaptive reactionless control algorithm to produce arm motions with minimal disturbance to the base. An online momentum-based estimation method was developed for inertia-parameter identification after capturing an unknown tumbling target. This approach ensures stability during the transition phase post-capture.
Raina et al. [110]	Reactionless control and adaptive reactionless control.	Stabilization and maneuvering of the target post-capture and handling unknown parameters.	The system's post-capture stabilization was achieved using reactionless control, which was also applied to maneuver the target post-capture. For targets with unknown parameters, adaptive reactionless control was utilized. The approach effectively handles post-capture stabilization but has limitations for large mass, high-speed objects, requiring joint constraints to avoid self-collision during post-capture motion.
Zhu et al. [111]	ASMDO and ATSMC.	Precise and fast trajectory tracking control for space manipulator post-capture.	The ASMDO estimates and rejects system uncertainties in finite time, even without knowledge of the derivative bounds of these uncertainties. The composite controller ensures that trajectory tracking errors converge to near zero in finite time while satisfying prescribed performance criteria.
Yan et al. [112]	Self-tuning controller (STC) and radial basis function controller (RBF).	Accurate trajectory tracking for transferring and detumbling a target.	A closed-loop dynamic model was developed for a space robot with 2 mission arms, evaluating the performance of STC, RBF, and a conventional computed torque adaptive controller. RBF is more effective for on-orbit transfer of known targets in the presence of significant external disturbances, whereas STC demonstrates better energy efficiency during on-orbit nonrotation tasks.

vibration suppression, finite-horizon path tracking, online adaptation, and error compensation.

Robust controllers, such as sliding mode control and its variants, improve system resilience but may compromise control accuracy. In contrast, model-free approaches, including RL and other data-driven methods, forgo the need for precise system modeling. However, these methods rely heavily on extensive training data to ensure consistent and effective performance, posing additional challenges in space robotics applications.

Table 7 summarizes more control strategies employed in post-capture operations for space robots, highlighting their methodologies, purposes, and key findings.

Ground Testing Simulation

Comprehensive ground experiments are vital for ensuring that a space manipulator and its associated control systems pass all verification tests before deployment. Ground-based testbeds have played a critical role in verifying spacecraft control hardware and software, ensuring reliability given the high costs and risks associated with on-orbit operations. To replicate the unique conditions of space, specialized testbed facilities have been developed in government and university laboratories, enabling realistic simulations of microgravity for thorough pre-launch testing [2].

Table 8 compares 5 prominent methods for testing space robots under microgravity conditions: air-bearing tables, suspension systems, airplane flying/free-falling motion, neutral buoyancy, and hybrid methods. This analysis highlights the strengths and limitations of each method, guiding the selection of the most suitable approach for specific space robotics applications.

Air-bearing tables, such as those used for testing the Space SRMS and other space robots, are widely utilized, as demonstrated by their application in various studies [50–53] due to their ability to provide reconfigurable, long-duration testing environments.

For instance, the RMS testbed developed by Space System Technology Centre (SSTC) includes a 4,200 mm by 3,600 mm granite table designed for the ground-based calibration of robotic systems [54]. However, while air-bearing table systems are effective for testing spacecraft control components like sensors and actuators, they are limited to 2-dimensional (2D) planar environments. To address rotational motion, spherical air bearings are commonly used for attitude control verification, offering low friction and torque-free environments. Despite these advantages, spherical air bearings have a limited motion range and are unsuitable for simulating flexible spacecraft appendages [55]. Combining planar and spherical air-bearing technologies could reproduce both rotational and translational motions, but achieving full 6-DOF remains a significant challenge.

An innovative approach to overcoming these limitations has been presented by Wei et al. [56], who combined suspension and air-bearing methods to create a more versatile ground microgravity experiment system. Their system not only compensates for the gravity of space manipulators moving in 3 dimensions without time limitations but also addresses the gravity of large-mass or high-inertia spacecraft. This hybrid approach significantly enhances the experimental capability of simulating microgravity conditions for complex space robotics applications.

In other studies, Rybus et al. [57] and Seweryn et al. [58] focused on air-bearing microgravity simulators specifically designed for testing OOS and active debris removal (ADR) missions. These simulators use planar environments to emulate the challenging task of capturing rotating targets, contributing valuable insights into the development of space robotics for these critical applications.

The neutral buoyancy method is commonly employed to simulate microgravity conditions for satellites. In some studies, electromagnets have been used to produce controllable electromagnetic forces, which, when combined with liquid buoyancy, enable large-scale and high-precision microgravity simulations. This method involves adjusting the counterweights in a pool until the buoyancy of the satellite is balanced with gravity, thereby allowing for 3D microgravity simulation tests.

Table 8. Comparison of methods used for testing space robots under microgravity conditions

Method	Description	Advantages	Disadvantages
Air-bearing tables	Typically used for planar systems but cannot replicate the 3D motion of space robots.	Suitable for planar systems.	Cannot replicate 3D motion.
Suspension system	Can test space robots in 3D.	Allows 3D testing.	Challenging to identify and compensate for kinetic friction; may become unstable due to coupled vibrations.
Airplane flying or free-falling motion	Achieves microgravity conditions using an airplane on a parabolic trajectory or a free-falling capsule at the Micro Gravity Center.	Observes pure mechanical behavior under natural microgravity conditions.	Expensive and inconvenient; short duration of microgravity; limitations on size and weight of the space robot.
Neutral buoyancy	Microgravity experiments conducted in a water pool using neutral buoyancy.	Unlimited duration of experiments.	Space-designed robots need custom-built prototypes to avoid water damage; fluid damping and inertia can corrupt results.
Hybrid method	Combines a mechanical model with a mathematical model.	Relatively inexpensive and easy to set up; precise dynamic model simulates space robotic system behavior.	Physical microgravity conditions are not replicated.

However, this approach requires modifications to the satellite's structure to make it waterproof, and the presence of water resistance and inertia can significantly compromise the accuracy of the test results.

Jin et al. [59] highlighted the importance of functional verification of space robots in neutral buoyancy systems for ground tests. They emphasized that determining the relative pose of a spacecraft is critical for the on-orbit operation of space robots. To address this, they developed a vision-based system for determining the relative pose of cooperative spacecraft within a neutral buoyancy environment, meeting the requirements for ground verification of on-orbit operations.

The 6-degree-of-freedom parallel mechanism, first proposed in 1965, has been a cornerstone of advanced mechanical systems due to its ability to precisely control multiple DOFs simultaneously. This mechanism consists of a fixed base and a movable platform connected by multiple parallel linkages, allowing for complex spatial motions. Its design offers advantages such as high rigidity, compact structure, and excellent positioning accuracy, making it suitable for applications requiring precise and dynamic motion control.

Despite these advantages, the parallel mechanism faces notable challenges in the context of microgravity simulation. Simultaneously achieving fast response, high precision, and the ability to handle large loads remains a significant hurdle. These challenges become critical when replicating the dynamics of space environments, where precise control and responsiveness are essential for effective testing.

To overcome these limitations, Jin et al. [59] developed a reconfigurable satellite ground microgravity simulation system based on a parallel mechanism (Fig. 6E). This system incorporates adjustable gravity coefficients and simulates 3D space movement with exceptional response speed and accuracy. It has been successfully applied to test the tolerance capabilities of reconfigurable satellite docking interfaces, providing a practical solution to the challenges of traditional microgravity simulation methods.

Integrating hardware testing with computer simulation provides a powerful method for validating the performance of space robots during intricate contact tasks. This approach, widely known as hardware-in-the-loop (HIL) simulation or hybrid simulation, enables the testing of complex systems by combining the physical and virtual aspects of robotic operations. HIL systems also complement digital twins (DTs), which are virtual representations of physical systems that mirror real-time operations through 2-way data exchange [60].

In space robotics, DTs play a crucial role in applications such as virtual test bed (VTB) implementations, haptic telerobotic assembly, telemetry data processing, and spacecraft maintenance. By integrating HIL systems and DTs, researchers can effectively verify the performance of space robots during complex tasks, ensuring both the accuracy and reliability of their operations [2].

However, HIL simulation has its limitations. First, the spacecraft or robot's mathematical model must be highly accurate, and real-time simulation is required to properly interact with the hardware. Second, the hardware must have sufficient bandwidth and impedance to replicate the real-space robot's dynamic behavior effectively. Lastly, the system must address time delays between hardware contact and the simulation-driven reaction, as opposed to the immediate passive reaction of the facility robot. Despite these challenges, HIL simulation remains an essential tool for testing and refining complex space systems [61].

Several significant works have been conducted in this area. Bai et al. [62] developed a hybrid simulator to improve the stability of space instable target simulators (SITSs), which are crucial for ground verification of on-orbit capture technology. Their system introduces a switching compensator with variable gain (SCVG) to correct input forces, enhancing simulation accuracy through numerical validation. Takahashi et al. [63] presented a hybrid simulator featuring a 14-DOF dual-arm robot and a 9-DOF motion table for ground verification of dual-arm space robots (Fig. 6F). This system effectively simulates complex collisions with multiple contacts, which are difficult to replicate through purely numerical simulations. Additionally, Xu et al. [64] designed an experimental setup incorporating 2 industrial robots, hand-eye and global cameras, and 5 industrial computers to emulate the capturing process, validating autonomous path planning and control algorithms for free-floating space robots (Fig. 6A).

Future Outlook

To address the increasing complexity (OOS) missions and the growing challenge of space debris removal, it is essential for space robotics technologies to evolve significantly. After a comprehensive review of key developments in space robotics and an in-depth analysis of the primary technologies and challenges they present, we propose that research should focus on several main areas, most of which are directly related to the improvement of space robotics.

Innovative Capture Mechanisms

Continuous innovation in capture mechanisms, leveraging soft robotics and bio-inspired designs, can enhance the safety and reliability of capturing space debris and malfunctioning satellites. Research could focus on developing resilient, multifunctional materials that can withstand the harsh conditions of space while providing capabilities like self-healing, high elasticity, and integrated sensing [65]. These advancements would significantly improve the autonomy of soft robots, enabling them to perform complex tasks in unstructured environments with greater adaptability and durability.

Advanced Dynamic Modeling and Control for Space Robots

Space robots are complex systems with dynamic, nonlinear interactions between their rigid and flexible components, making them highly coupled systems. Due to these complexities, future research should prioritize the development of more accurate and comprehensive dynamic models. These models need to incorporate the various uncertainties and disturbances encountered in real-space environments—such as dynamic gravitational fields, space radiation, micrometeoroid impacts, and thermal fluctuations—to better simulate real mission conditions. Addressing the strong coupling between control mechanisms and dynamic properties is crucial for enhancing performance, especially as space robots are required to operate over broader ranges, carry increased loads, and achieve higher precision in future OSS (on-orbit servicing) missions.

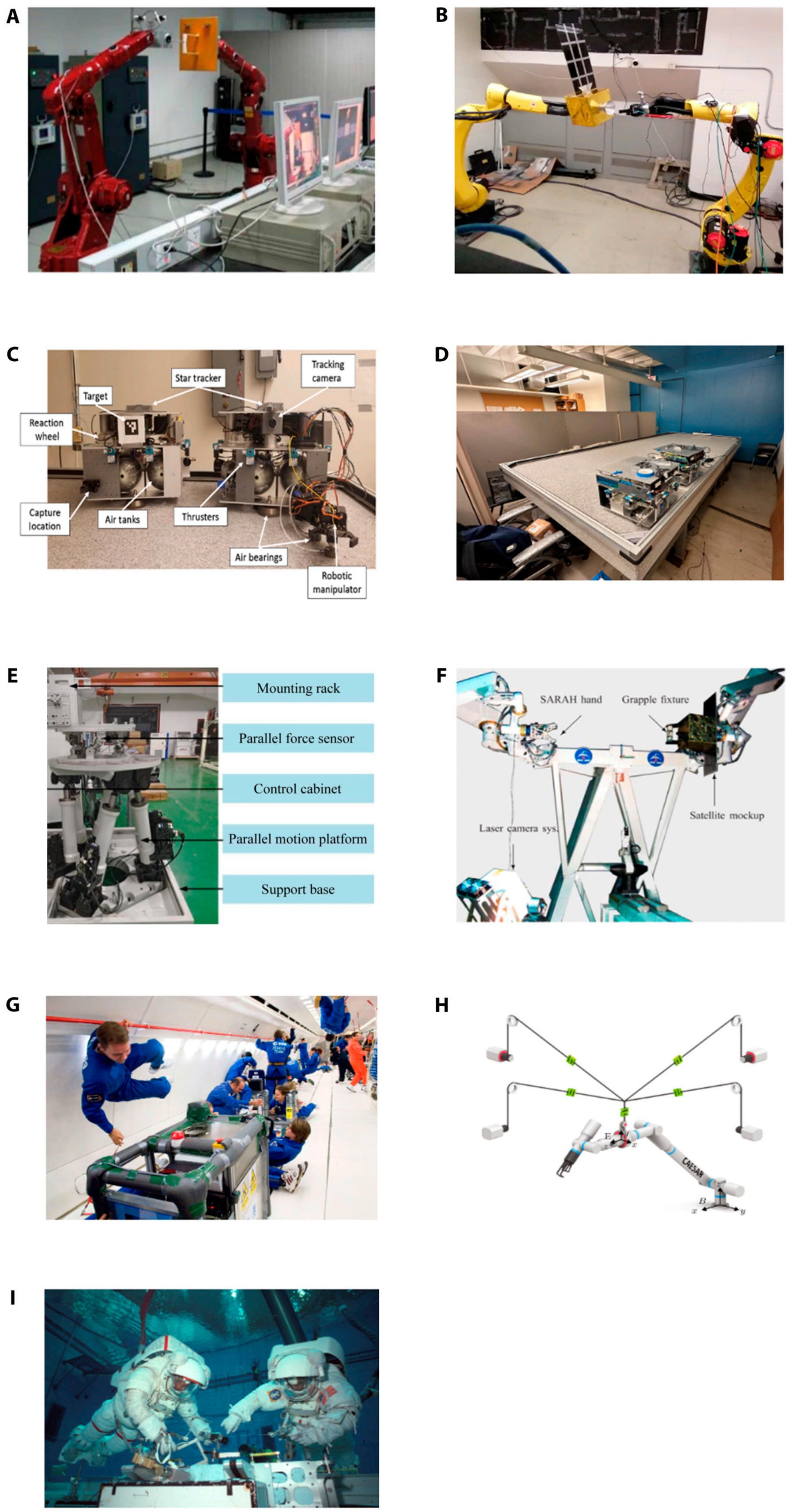

Fig. 6. (A) Ground experimental system [61]. (B) Hardware-in-the-loop ground testbed [61]. (C) Planar air-bearing simulator [1]. (D) Air-bearing testbed at York University. (E) Microgravity simulation system [59]. (F) Hybrid simulator [1]. (G) Parabolic flights [69]. (H) A cable-driven parallel robot can be used for suspending a space robot arm [70]. (I) Mission specialist Doi during EVA training at Johnson Space Center (JSC) Neutral Buoyancy Laboratory (NBL) [71].

In addition to refining dynamic models, incorporating advanced nonlinear control strategies and leveraging machine learning can further enhance control without relying solely on detailed dynamic models. Machine learning approaches, which do not depend on precise dynamic models when applied to robot control, can enable autonomous intelligent control. As a result, machine learning offers great potential to improve the control capabilities of space robots, enabling more intelligent and adaptable operations. These combined approaches will allow researchers to emulate mission conditions more faithfully, provide deeper insights, and better prepare space manipulators for the unpredictability of space.

Advanced Pre-Capture Phase

In future works, trajectory planning research is expected to increasingly integrate machine learning, marking a significant advancement in intelligent planning methodologies. The incorporation of machine learning and other AI technologies holds the potential to greatly enhance the adaptability, efficiency, and overall intelligence of trajectory planning systems. By leveraging data-driven optimization, these methods can learn from past experiences and continuously refine planning strategies, paving the way for more innovative and effective solutions.

Machine learning also enables trajectory planning systems to adapt to dynamic and uncertain environments, a critical capability for applications such as space robotics, autonomous vehicles, and industrial automation. Furthermore, AI-powered algorithms facilitate real-time decision-making, allowing for trajectory adjustments to handle unexpected changes or disturbances with precision and robustness. Looking ahead, research could explore how machine learning can be seamlessly integrated with other systems, such as compliance control, obstacle avoidance, and multi-objective optimization, to create unified and efficient frameworks. However, while the potential is immense, challenges such as the need for extensive computational resources, ensuring data quality, and maintaining reliability in safety-critical applications must be addressed to fully realize these advancements.

In addition to advancements in motion planning, future research on pre-capturing phases should focus on enhancing vision-based techniques, which play a critical role in tasks such as pose estimation, motion tracking, and target identification. The integration of DL methods with visual systems holds significant promise for improving the accuracy and robustness of visual-based estimation. However, most publications currently explore the application of DL in space from a theoretical perspective, often overlooking computational performance considerations. Only a limited number of studies address the practical deployment of DL techniques on hardware, considering factors such as execution time and the size of training datasets.

Advanced Post-Capture Phase

In future works, research is expected to focus on the integration of AI technologies, particularly RL, imitation learning, and other AI-driven methods, to manage noncooperative targets more effectively. These techniques can enable adaptive and efficient control without relying on precise dynamic models, making them ideal for handling unpredictable target behaviors. Another promising direction is hybrid validation techniques, such as combining HIL simulations with DT technology. These approaches enable detailed real-time analysis and testing of robotic performance under various conditions, significantly enhancing the reliability and accuracy of control systems.

Developing dynamic adaptation capabilities in control systems is also a critical area for future research. This involves designing systems that can respond to unexpected changes in target behavior or environmental conditions using robust control algorithms and real-time feedback. Furthermore, the exploration of collaborative robotics presents opportunities for distributed stabilization and manipulation tasks. Multi-robot systems could work together to manage large or complex targets, improving overall efficiency and reducing operational demands.

By addressing these areas, researchers can overcome existing limitations and advance the capabilities of space robotics in the post-capture phase.

Advanced Realistic Environmzental Simulation

Future advancements in simulation technologies for space robotics will likely focus on enhancing fidelity, versatility, and cost-effectiveness. A major challenge in this field is bridging the reality gap—the disparity between simulation environments and real-world applications. To address this, researchers are exploring innovative solutions to create more accurate and adaptable testing environments.

One promising approach is the combination of different ground testbeds, such as integrating air-bearing tables with suspension systems. This hybrid approach leverages the complementary strengths of individual testbeds, enabling full 6-DOF simulations and addressing the limitations of standalone methods. By combining these technologies, researchers can create more comprehensive simulation platforms that better replicate space conditions.

In parallel, the use of DTs is gaining traction as a cutting-edge solution. These high-fidelity virtual models replicate the properties, behaviors, and dynamics of physical systems in real time, allowing for the simulation and analysis of robot performance under conditions such as microgravity, space radiation, micrometeoroid impacts, and thermal fluctuations—all without the need for physical testing in space. DTs significantly enhance the reliability and effectiveness of robotic systems in actual missions.

Additionally, advanced techniques such as domain randomization, domain adaptation, imitation learning, and transfer learning are being explored to reduce the reality gap. These methods enable pre-trained models to adapt to new environments, improving the stability and performance of robotic applications in real-world space missions. Collectively, these advancements will play a crucial role in preparing space robotics for the complex and unpredictable conditions of space exploration.

Conclusion

This review provides an overview of ADR and OOS missions, highlighting their significance in addressing the growing challenges of space debris and satellite maintenance. It further explores recent advancements in capturing techniques developed over the years, showcasing a variety of grippers designed for ADR and OOS applications. Significant progress in control strategies across the 3 distinct phases of space robotic operations—pre-capturing, capturing, and post-capturing—has shown great potential in overcoming the challenges associated with these missions. Additionally, the paper examines major ground-based testing and verification facilities established worldwide to support on-orbit robotic capture and servicing operations. It also highlights upcoming space debris removal missions planned for the near future, reflecting the growing global commitment to addressing space debris. Despite significant recent advancements, several critical challenges remain unresolved and require further investigation to ensure the safe and successful deployment of robotic systems in orbit.

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Data Availability

The data used to support the findings of this study are available from the author upon reasonable request.

References

1. Alizadeh M, Zhu ZH. A comprehensive survey of space robotic manipulators for on-orbit servicing. *Front Robot AI*. 2024;11:1470950.
2. Flores-Abad A, Ma O, Pham K, Ulrich S. A review of space robotics technologies for on-orbit servicing. *Prog Aerosp Sci*. 2014;68:1–26.
3. Wang X, Shi L, Katupitiya J. A strategy to decelerate and capture a spinning object by a dual-arm space robot. *Aerosp Sci Technol*. 2021;113:Article 106682.
4. Papadopoulos E, Aghili F, Ma O, Lampariello R. Robotic manipulation and capture in space: A survey. *Front Robot AI*. 2021;8:Article 686723.
5. Canadian Space Agency, About Canadarm2. [accessed 22 Nov 2024] https://www.asc-csa.gc.ca/eng/iss/canadarm2/about.asp.
6. Canadian Space Agency, About Dextre. [accessed 22 Nov 2024] https://www.asc-csa.gc.ca/eng/iss/dextre/about.asp.
7. eoPortal, ISS: ERA (European Robotic Arm). [accessed 22 Nov 2024] https://www.eoportal.org/satellite-missions/iss-era#references.
8. Japan Aerospace Exploration Agency, Japanese Experiment Module Remote Manipulator System.
9. Robonaut. [accessed 22 Nov 2024] https://www.nasa.gov/robonaut2/.
10. Matsumoto S, Ohkami Y, Wakabayashi Y, Oda M, Ueno H, Satellite capturing strategy using agile Orbital Servicing Vehicle, Hyper-OSV. Paper presented at: Proceedings 2002 IEEE International Conference on Robotics and Automation (Cat. No.02CH37292); 2002 May 11–15; Washington, DC, USA.
11. D. Reintsema, J. Thaeter, A. Rathke, W. Naumann, P. Rank, J. Sommer, DEOS—The German robotics approach to secure and de-orbit malfunctioned satellites from low earth orbits. In: *Proceedings of the i-SAIRAS*. Japan: Japan Aerospace Exploration Agency (JAXA); 2010.
12. R. Biesbroek, L. Innocenti, A. Wolahan, S. M. Serrano, e.Deorbit—ESA's active debris removal mission. In: *Proceedings of the 7th European Conference on Space Debris*. Darmstadt (Germany): ESA Space Debris Office; 2017.
13. Honeybee Robotics, On-orbit satellite servicing tools. https://www.honeybeerobotics.com/Products/on-Orbit-Satellite-Servicing-Tools/.
14. Duke H. On-orbit servicing. *Cent Strateg Int Stud*. 2021.
15. Li D, Wang Y, Overview of the Chinese space station manipulator. Paper presented at: AIAA SPACE 2015 Conference and Exposition; 2015 Aug 31–Sep 2; Pasadena, CA, USA.
16. Feng F, Tang L, Xu J, Liu H, Liu Y. A review of the end-effector of large space manipulator with capabilities of misalignment tolerance and soft capture. *Sci China Technol Sci*. 2016;59(11):1621–1638.
17. Canadian Space Agency, Canada begins design phase of Canadarm3 for Lunar Gateway. [accessed 22 Nov 2024] https://www.canada.ca/en/space-agency/news/2022/03/canada-begins-design-phase-of-canadarm3-for-lunar-gateway.html.
18. Shan M, Guo J, Gill E. Review and comparison of active space debris capturing and removal methods. *Prog Aerosp Sci*. 2016;80:18–32.
19. Zhang W, Li F, Li J, Cheng Q. Review of on-orbit robotic arm active debris capture removal methods. *Aerospace*. 2022;10(1):13.
20. Yao Q. Adaptive trajectory tracking control of a free-flying space manipulator with guaranteed prescribed performance and actuator saturation. *Acta Astronaut*. 2021;185:283–298.
21. Han D, Liu Z, Huang P. Capture and detumble of a non-cooperative target without a specific gripping point by a dual-arm space robot. *Adv Space Res*. 2022;69(10):3770–3784.
22. Han D, Dong G, Huang P, Ma Z. Capture and detumbling control for active debris removal by a dual-arm space robot. *Chin J Aeronaut*. 2022;35(9):342–353.
23. Shi J-F, Ulrich S, Allen A, Spacecraft adaptive attitude control with application to space station free-flyer robotic capture. Paper presented at: AIAA Guidance, Navigation, and Control Conference; 2015; Kissimmee, FL, USA.
24. Xu S, Chen T, Wen H, Jin D. Predefined-time tracking control of a free-flying space robot on SE(3). *IEEE Trans Aerosp Electron Syst*. 2024;60(5):5906–5919.
25. Shibabw EW, Tamiru GY, Fuzzy sliding mode controller based trajectory tracking control of free flying space robot manipulator system. In: Woldegiorgis BH, Mequanint K, Bitew MA, Beza TB, Yibre AM, editors, *Artificial intelligence and digitalization for sustainable development*. Cham: Springer Nature Switzerland; 2023. p. 137–158.
26. Mohamed A, Saaj C, Seddaoui A. Linear controllers for free-flying and controlledfloating space robots: A new perspective. *Aeronaut Aerosp Open Access J*. 2020;4(3):97–114.
27. Ali A, Shi J-F, Zhu ZH. Path planning of 6-DOF free-floating space robotic manipulators using reinforcement learning. *Acta Astronaut*. 2024;224:367–378.

28. Guo Z, Ju H, Lu C, Wang K. Dynamic modeling and improved nonlinear model predictive control of a free-floating dual-arm space robot. *Appl Sci*. 2024;14(8):3333.
29. Fu X, Ai H, Chen L. Repetitive learning sliding mode stabilization control for a flexible-base, flexible-link and flexible-joint space robot capturing a satellite. *Appl Sci*. 2021;11(17):8077.
30. Fehse W (Ed). Automated rendezvous and docking of spacecraft. In: *Cambridge aerospace series no. 16*. Cambridge (NY): Cambridge University Press; 2003.
31. Rybus T, Prokopczuk J, Wojtunik M, Aleksiejuk K, Musiał J. Application of bidirectional rapidly exploring random trees (BiRRT) algorithm for collision-free trajectory planning of free-floating space manipulator. *Robotica*. 2022;40(12): 4326–4357.
32. Wang M, Luo J, Walter U. Trajectory planning of free-floating space robot using particle swarm optimization (PSO). *Acta Astronaut*. 2015;112:77–88.
33. Zhang S, Xia Q, Chen M, Cheng S. Multi-objective optimal trajectory planning for robotic arms using deep reinforcement learning. *Sensors*. 2023;23(13):5974.
34. Beigomi B, Zhu ZH. Towards real-world efficiency: Domain randomization in reinforcement learning for pre-capture of free-floating moving targets by autonomous robots. In: *In: 2024 IEEE International Conference on Robotics and Automation (ICRA)*. Yokohama (Japan): IEEE; 2024. p. 11753–11759.
35. Srivastava R, Lima R, Sah R, Das K. Deep reinforcement learning based control of rotation floating space robots for proximity operations in PyBullet. In: *In: 2023 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*. Honolulu (HI): IEEE; 2023. p. 1224–1229.
36. Wang S, Zheng X, Cao Y, Zhang T. A multi-target trajectory planning of a 6-DoF free-floating space robot via reinforcement learning. In: *In: 2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS). Prague* (Czech Republic): IEEE; 2021. p. 3724–3730.
37. Chen Z, Zhou W. Path planning for a space-based manipulator system based on quantum genetic algorithm. *J Robot*. 2017;2017(1):Article 3207950.
38. Hirano D, Kato H, Saito T. Online path planning and compliance control of space robot for capturing tumbling large object. In: *In: 2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. Madrid: IEEE; 2018. p. 2909–2916.
39. Larouche BP, Zhu ZH. Position-based visual servoing in robotic capture of moving target enhanced by Kalman filter. *Int J Robot Autom*. 2015;30(3).
40. Mishra H, Schmidt P, Motion and parameter estimation for the robotic capture of a non-cooperative space target considering egomotion uncertainty. Paper presented at: Proc. 14th Symp. on Advanced Space Technologies in Robotics and Automation (ASTRA); 2017; Leiden, The Netherlands.
41. Dong G, Zhu ZH. Autonomous robotic capture of non-cooperative target by adaptive extended Kalman filter based visual servo. *Acta Astronaut*. 2016;122:209–218.
42. Dong G, Zhu ZH. Incremental inverse kinematics based vision servo for autonomous robotic capture of non-cooperative space debris. *Adv Space Res*. 2016;57(7):1508–1514.
43. Sonawani S, Alimo R, Detry R, Jeong D, Hess A, Amor HB, Assistive relative pose estimation for on-orbit assembly using convolutional neural networks. arXiv. 2020. https://doi.org/10.48550/arXiv.2001.10673.
44. Guthrie B, Kim M, Urrutxua H, Hare J. Image-based attitude determination of co-orbiting satellites using deep learning technologies. *Aerosp Sci Technol*. 2022;120:Article 107232.
45. Jankovic M, Yüksel M, Babr MM, Letizia F, Braun V. Space debris ontology for ADR capture methods selection. *Acta Astronaut*. 2020;173:56–68.
46. Li S, She Y. Recent advances in contact dynamics and post-capture control for combined spacecraft. *Prog Aerosp Sci*. 2021;120:Article 100678.
47. Ma Z, Wang Y, Yang Y, Wang Z, Tang L, Ackland S. Reinforcement learning-based satellite attitude stabilization method for non-cooperative target capturing. *Sensors*. 2018;18(12):4331.
48. Vyas S, Maywald L, Kumar S, Jankovic M, Mueller A, Kirchner F. Post-capture detumble trajectory stabilization for robotic active debris removal. *Adv Space Res*. 2023;72(7):2845–2859.
49. Huang X, Biggs JD, Duan G. Post-capture attitude control with prescribed performance. *Aerosp Sci Technol*. 2020;96:Article 105572.
50. Santaguida L, Zhu ZH. Development of air-bearing microgravity testbed for autonomous spacecraft rendezvous and robotic capture control of a free-floating target. *Acta Astronaut*. 2023;203:319–328.
51. Yalçın BC, Martinez C, Coloma S, Skrzypczyk E, Olivares-Mendez MA. Lightweight floating platform for ground-based emulation of on-orbit scenarios. *IEEE Access*. 2023;11:94575–94588.
52. Meng Q, Zhao C, Ji H, Liang J. Identify the full inertial parameters of a non-cooperative target with eddy current detumbling. *Adv Space Res*. 2020;66(7):1792–1802.
53. Schlotterer M, Theil S. Testbed for on-orbit servicing and formation flying dynamics emulation. In: *AIAA Modeling and Simulation Technologies Conference*. Toronto (Ontario, Canada): American Institute of Aeronautics and Astronautics; 2010.
54. Xu W, Liang B, Xu Y. Survey of modeling, planning, and ground verification of space robotic systems. *Acta Astronaut*. 2011;68(11–12):1629–1649.
55. Schwartz JL, Peck MA, Hall CD. Historical review of air-bearing spacecraft simulators. *J Guid Control Dyn*. 2003;26(4):513–522.
56. Wei Y, Yang X, Xu Z, Bai X. Novel ground microgravity experiment system for a spacecraft-manipulator system based on suspension and air-bearing. *Aerosp Sci Technol*. 2023;141:Article 108587.
57. Rybus T, Seweryn K, Oleś J, Basmadji FL, Tarenko K, Moczydłowski R, Barciński T, Kindracki J, Mężyk Ł, Paszkiewicz P, et al. Application of a planar air-bearing microgravity simulator for demonstration of operations required for an orbital capture with a manipulator. *Acta Astronaut*. 2019;155:211–229.
58. Seweryn K, Rybus T, Colmenarejo P, Novelli G, Oles J, Pietras M, Sasiadek JZ, Scheper M, Tarenko K. Validation of the robot rendezvous and grasping manoeuvre using microgravity simulators. In: *In: 2018 IEEE International Conference on Robotics and Automation (ICRA)*. Brisbane (QLD): IEEE; 2018. p. 873–880.
59. Jin J, Sun X, Yu D, Chen Z. Research on ground microgravity simulation system based on parallel mechanism. *Microgravity Sci Technol*. 2024;36(1):5.

60. Mazumder A, Sahed MF, Tasneem Z, Das P, Badal FR, Ali MF, Ahamed MH, Abhi SH, Sarker SK, Das SK, et al. Towards next generation digital twin in robotics: Trends, scopes, challenges, and future. *Heliyon*. 2023;9(2):Article e13359.
61. Ali AA, Beigomi B, Zhu ZH. Development of 6DOF hardware-in-the-loop ground testbed for autonomous robotic space debris removal. *Aerospace*. 2024;11(11):877.
62. Bai X, Li X, Zhao Z, Xu Z, Lu H, Liu M. Stability analysis and delay compensation for space instable target simulator. *Actuators*. 2024;13(4):123.
63. Takahashi R, Ise H, Konno A, Uchiyama M, Sato D. Hybrid simulation of a dual-arm space robot colliding with a floating object. In: *In: 2008 IEEE International Conference on Robotics and Automation*. Pasadena (CA): IEEE; 2008. p. 1201–1206.
64. Xu W, Liang B, Li C, Liu Y, Xu Y. Autonomous target capturing of free-floating space robot: Theory and experiments. *Robotica*. 2009;27(3):425–445.
65. Zhang Y, Li P, Quan J, Li L, Zhang G, Zhou D. Progress, challenges, and prospects of soft robotics for space applications. *Adv Intell Syst*. 2023;5(3):2200071.
66. T. Brazda, NASA's Robonaut2. https://www.nasa.gov/general/nasas-robonaut-legs-headed-for-international-space-station/.
67. Ma B, Jiang Z, Liu Y, Xie Z. Advances in space robots for on-orbit servicing: A comprehensive review. *Adv Intell Syst*. 2023;5(8):2200397.
68. Yang J, Ren C, Yang C, Wang Y, Wan S, Kang R. Design of a flexible capture mechanism inspired by sea anemone for non-cooperative targets. *Chin J Mech Eng*. 2021;34(1):77.
69. Landmark flight for ESA's microgravity research. https://www.esa.int/Science_Exploration/Human_and_Robotic_Exploration/Research/Landmark_flight_for_ESA_s_microgravity_research.
70. Elhardt F, Boumann R, De Stefano M, Heidel R, Lemmen P, Heumos M, Jeziorek C, Roa MA, Schedl M, Bruckmann T, Correction to: The Motion Suspension System—MSS: A cable-driven system for on-ground tests of space robots. In: M. Okada, editor. *Advances in mechanism and machine science*, vol. 148. Cham: Springer Nature Switzerland; 2024.
71. Japan Aerospace Agency, Mission specialist Doi during EVA training at Johnson Space Center (JSC) Neutral Buoyancy Laboratory (NBL). https://iss.jaxa.jp/shuttle/flight/sts87/sts87photo_training_e.html.
72. Matsushita T, Yoshida K, Experimental verification on caging-capture of a free-floating object by a dual-arm space robot. 2020.
73. Zhang X, Liu J, Feng J, Liu Y, Ju Z. Effective capture of nongraspable objects for space robots using geometric cage pairs. *IEEEASME Trans Mechatron*. 2020;25(1):95–107.
74. Sun Y, Wang Q, Jiao R, Liu R, Jin M. Design of a non-cooperative target capture mechanism for capturing satellite launch adapter ring. *Proc Inst Mech Eng G J Aerosp Eng*. 2023;237(5):1060–1077.
75. Zhang G, Zhang Q, Feng Z, Chen Q, Yang T. Dynamic modeling and simulation of a novel mechanism for adhesive capture of space debris. *Adv Space Res*. 2021;68(9):3859–3874.
76. Hawkes EW, Jiang H, Cutkosky MR. Three-dimensional dynamic surface grasping with dry adhesion. *Int J Robot Res*. 35(8):943–958.
77. Li X, Sun K, Liu H. Design of a novel deployable mechanism for capturing tumbling debris. *Trans Can Soc Mech Eng*. 2019;43(3):294–305.
78. Cao Y, Wang S, Zheng X, Ma W, Xie X, Liu L. Reinforcement learning with prior policy guidance for motion planning of dual-arm free-floating space robot. *Aerosp Sci Technol*. 2023;136:Article 108098.
79. Li Y, Hao X, She Y, Li S, Yu M. Constrained motion planning of free-float dual-arm space manipulator via deep reinforcement learning. *Aerosp Sci Technol*. 2021;109: Article 106446.
80. Psomiadis E, Papadopoulos E. Model-based/model predictive control design for free floating space manipulator systems. In: *In: 2022 30th Mediterranean Conference on Control and Automation (MED)*. Vouliagmeni (Greece): IEEE; 2022. p. 847–852.
81. Rybus T, Seweryn K, Sasiadek JZ. Control system for free-floating space manipulator based on nonlinear model predictive control (NMPC). *J Intell Robot Syst*. 2017;85(3–4): 491–509.
82. Shang D, Li X, Yin M, Li F. Dynamic modeling and RBF neural network compensation control for space flexible manipulator with an underactuated hand. *Chin J Aeronaut*. 2024;37(3):417–439.
83. Dou B, Yue X. Disturbance observer-based fractional-order sliding mode control for free-floating space manipulator with disturbance. *Aerosp Sci Technol*. 2023;132: Article 108061.
84. Xie L, Yu X. State observer based robust backstepping fault-tolerant control of the free-floating flexible-joint space manipulator. *Appl Sci*. 2023;13(4):2634.
85. Yan W, Liu Y, Lan Q, Zhang T, Tu H. Trajectory planning and low-chattering fixed-time nonsingular terminal sliding mode control for a dual-arm free-floating space robot. *Robotica*. 2022;40(3):625–645.
86. Vyas S, Wehbe B, Kumar S, Quaternion based LQR for free-floating robots without gravity. Paper presented at: Proc. CEAS EuroGNC 2022; 2022; Lille, France.
87. Xie Z, Sun T, Kwan TH, Mu Z, Wu X. A new reinforcement learning based adaptive sliding mode control scheme for free-floating space robotic manipulator. *IEEE Access*. 2020;8:127048–127064.
88. Tavana S, Faghihi S, de Ruiter A, Kumar KD, A novel optimization-based collision avoidance for autonomous on-orbit assembly. arXiv. 2024. https://doi.org/10.48550/arXiv.2404.07916.
89. Zhang Q, Liu Y, Qin J, Duan J. An informed-bi-quick RRT* algorithm based on offline sampling: Motion planning considering multiple constraints for a dual-arm cooperative system. *Actuators*. 2024;13(2):75.
90. Faghihi S, Tavana S, De Ruiter AHJ. Kinodynamic on-orbit inspection path planning for full-coverage inspection in close proximity of space structures. *Acta Astronaut*. 2022;198:354–365.
91. Basmadji FL, Seweryn K, Sasiadek JZ. Space robot motion planning in the presence of nonconserved linear and angular momenta. *Multibody Syst Dyn*. 2020;50(1):71–96.
92. Zhang X, Liu J. Effective motion planning strategy for space robot capturing targets under consideration of the berth position. *Acta Astronaut*. 2018;148:403–416.
93. James F, Shah SV, Singh AK, Krishna KM, Misra AK. Reactionless maneuvering of a space robot in precapture phase. *J Guid Control Dyn*. 39(10):2419–2425.
94. Li K, Xu F, Zhang H, Wang H. Visual servoing of flexible manipulators with unknown camera intrinsic parameters

and vibration states. *IEEEASME Trans Mechatron*. 2024;29(1):510–520.
95. Tang C, Yao J, Liang L, Zhang H, Wei C, Zhao Y. Estimation of full dynamic parameters of large space debris based on rope net flexible collision and vision. *Actuators*. 2023;12(9):344.
96. Aghili F. Fault-tolerant and adaptive visual servoing for capturing moving objects. *IEEEASME Trans. Mechatron.* 2022;27(3):1773–1783.
97. Al-Shanoon A, Lang H. Robotic manipulation based on 3-D visual servoing and deep neural networks. *Robot Auton Syst*. 2022;152:Article 104041.
98. Ribeiro EG, De Queiroz Mendes R, Grassi V. Real-time deep learning approach to visual servo control and grasp detection for autonomous robotic manipulation. *Robot Auton Syst*. 2021;139:Article 103757.
99. Kobayashi T, Nishida S-I, Nakamura S, Nakatani S. Study of image processing methods for space debris capture. In: *In: 2021 IEEE/SICE International Symposium on System Integration (SII).* Iwaki (Fukushima, Japan): IEEE; 2021. p. 304–309.
100. Luo B, Chen H, Quan F, Zhang S, Liu Y. Natural feature-based visual servoing for grasping target with an aerial manipulator. *J Bionic Eng*. 2020;17(2):215–228.
101. Dong G, Zhu ZH. Kinematics-based incremental visual servo for robotic capture of non-cooperative target. *Robot Auton Syst*. 2019;112:221–228.
102. H. Mishra, M. De Stefano, A. M. Giordano, C. Ott, A nonlinear observer for free-floating target motion using only pose measurements. I*n: 2019 American Control Conference (ACC)*. Philadelphia (PA): IEEE; 2019. p. 1114–1121.
103. Christidi-Loumpasefski OO, Papadopoulos E, Parameter identification of a space object in the pre-capture phase. Paper presented at: Proc. Int. Symp. on Artificial Intelligence, Robotics and Automation in Space (i-SAIRAS); 2018; Madrid, Spain.
104. Lampariello R, Mishra H, Oumer N, Schmidt P, De Stefano M, Albu-Schaffer A. Tracking control for the grasping of a tumbling satellite with a free-floating robot. *IEEE Robot Autom Lett*. 2018;3(4):3638–3645.
105. Larouche BP, Zhu ZH. Autonomous robotic capture of non-cooperative target using visual servoing and motion predictive control. *Auton Robot*. 2014;37(2):157–167.
106. Tzschichholz T, Ma L, Schilling K. Model-based spacecraft pose estimation and motion prediction using a photonic mixer device camera. *Acta Astronaut*. 2011;68(7–8):1156–1167.
107. Chen S, Yuan J, Wang Z, Zhu Z. Partial stabilization of underactuated post-capture combination with inaccurate measurement information and unknown disturbances. *Trans Inst Meas Control*. 2018;40(13):3625–3639.
108. Zhang Z, Li X, Wang X, Zhou X, An J, Li Y. TDE-based adaptive integral sliding mode control of space manipulator for space-debris active removal. *Aerospace*. 2022;9(2):105.
109. Nguyen-Huynh TC, Sharf I. Adaptive reactionless motion and parameter identification in postcapture of space debris. *J Guid Control Dyn*. 2013;36(2):404–414.
110. Raina D, Gora S, Maheshwari D, Shah SV. Impact modeling and reactionless control for post-capturing and maneuvering of orbiting objects using a multi-arm space robot. *Acta Astronaut*. 2021;182:21–36.
111. Zhu Y, Qiao J, Guo L. Adaptive sliding mode disturbance observer-based composite control with prescribed performance of space manipulators for target capturing. *IEEE Trans Ind Electron*. 2019;66(3):1973–1983.
112. Yan X, Shan M, Shi L. Adaptive and intelligent control of a dual-arm space robot for target manipulation during the post-capture phase. *Aerosp Sci Technol*. 2023;142:Article 108688.