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Review

Review of On-Orbit Robotic Arm Active Debris Capture Removal Methods

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Abstract: Space is the driving force of the world's sustainable development, and ensuring the sustainability of human activity in space is also necessary. Robotic arm active debris capture removal (RA-ADCR) is a noteworthy technology for containing the dramatic increase in space debris and maintaining orbital safety. This review divides the RA-ADCR technology progress history into three periods and presents the status of related research. Two major development trends are summarized and subdivided through the analysis and collation of research achievements over the past three years. Taking the treatment of parameter uncertainties as the entry point, researchers would like to improve the discrimination accuracy and scope to reduce uncertainties. On the other hand, researchers accept such uncertainties and would like to offset and avoid the impact of uncertainties by extending the error margins. Subsequently, the challenges of RA-ADCR are analyzed in line with the task execution flow, which mainly focuses on the conflict between on-satellite computing power and the performance of task execution. In addition, feasible solutions for the current phase are discussed. Finally, future outlooks are evaluated and discussed.

Keywords: active debris removal; on-orbit servicing; capture removal; robotic arm; uncertainty

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1. Introduction

The United Nations identified the Earth's orbital space environment as a finite resource in its Guidelines for the Long-term Sustainability of Outer Space Activities [1,2]. However, such a limited resource will likely become scarce in recent years with the deployment of constellations such as StarLink, OneWeb, LeoSat, and TeleSat. Space is the driver of the world's sustainable development [3], and ensuring the sustainability of human activity in space is also necessary. Along with the need for continued economic progress, the balance between the increasingly scarce Earth orbit resources and increasingly frequent space missions has become an important topic. As of May 2022, an estimated 5800 satellites were orbiting the Earth, compared to only 2290 in 2019. Although launch technological innovations such as one-rocket-launch multi-satellites have led to an increased share of payloads in orbit, the increase only covers between 10.4% and 15.9%. Those objects, other than payloads, are defined as space debris. Such high-velocity and uncontrolled space debris can severely affect spacecraft and the space environment. For example, debris of approximately 10 cm can destroy any operational satellite in the event of a collision and create thousands of pieces of space debris in orbit, which will remain in orbit for years or even decades [4].

Sixteen years ago, Liou [5,6] noted that even if there were no more satellite launches, the amount of space debris would remain relatively stable for only approximately 50 years. Nevertheless, as of May 2022, the ESA has detected and tracked 36,500 pieces of space debris larger than 10 cm, weighing nearly 10,000 tons, which is already four times the number 16 years ago [7]. Fortunately, we have not yet triggered Kessler syndrome [8], a phenomenon in which debris from collisions explodes when it hits other objects, creating new debris that hits other objects. However, 11.7 unintentional fragmentation events per year imply that we are most likely approaching the Kessler limit [7,9].

In response to the continuing severe space debris crisis, many international organizations have made efforts toward sustainable space development. International conferences such as the COSPAR, IAC, and IAASS conferences have been exploring solutions to the space debris problem since 1984. In 1993, the establishment of IADC, an international organization, marked the completion of a communication platform dedicated to space debris mitigation. The United Nations Committee on the Peaceful Uses of Outer Space took long-term outer space sustainability as an agenda item in 2010 and adopted the relevant guidelines in 2019 [10]. ESA, the agency most concerned with space debris and its removal methods, has even established a space debris office to coordinate related research.

There are two main approaches to mitigating the dramatic increase in space debris [11]. One is the rational design of space systems, ensuring that they do not become space debris in the future. The above design must avoid in-orbit disintegration and collision scenarios during mission execution and active disposal efforts after mission execution. The other is using active debris removal techniques to dispose of space debris that is not capable of autonomous destruction. NASA and the ESA have stated that at least five large space debris targets must be removed yearly to maintain the orbital environment [12]. The RA-ADCR method is an important branch in developing active debris removal technology. Compared with non-capture techniques, such as using an ion beam to "push" debris, which will consume 40 W/mN of electrical power over a long period of time, the RA-ADCR method requires low power consumption and is compatible with microsatellites [13]. In addition, grasping by arms has been considered the more mature technology. Compared with other capture techniques, such as tethered net systems, it has a high fault tolerance rate, which provides higher controllability and safety for implementation [14].

There are also previous reviews related to the field of active debris [15,16]. Compared with previous work, this review focuses on the robotic arm active debris capture direction in the above field. In addition, this paper has the following advantages: a clearer overview of development in the field, a new perspective on the field development trends, and more cutting-edge research publications.

This review presents the RA-ADCR technology in seven parts. The first section introduces the background, significance, and urgency of the research. The following section gives statistics on the relevant literature in the mentioned field and analyses the literature partnerships and research hotspots. With 2019 as the dividing year, this review discusses the historical development process from 1983 to 2018 in three periods. Sections 3 and 4 provide an overview of the last three years of research in response to the two different trends in dealing with uncertainties. The fifth section analyzes the challenge of the RA-ADCR field that balances computing power limitations with task execution effectiveness. The sixth section provides an outlook on the advanced direction of the RA-ADCR field. The final section concludes the entire work.

2. Research Progress Analysis

This section presents an analysis of the historical research aspects of RA-ADCR technology based on previous publications. The literature data were collected using the WOS core library by searching for the themes of 'space manipulator', 'capture', and 'non-cooperative'. The search was conducted for the period 1983–2022, with the dataset collected on 15 July 2022. A total of 539 valid documents were obtained by screening for non-relevant content and a histogram of the temporal distribution of documents for the period 1992–2022, as shown in Figure 1.

The orange part is the actual annual number of papers in the RA-ADCR field, while the gray part is the forecast based on the current papers until the end of 2022. The trend line for the number of publications was obtained using a four-period average method. The graph visualizes that the number of papers in the field increased significantly since 2006 and peaked in 2019. Regarding the trend line, there has been an exponential increase in the number of RA-ADCR technology research results, which indicates that researchers have shown great interest and enthusiasm in the field of RA-ADCR.

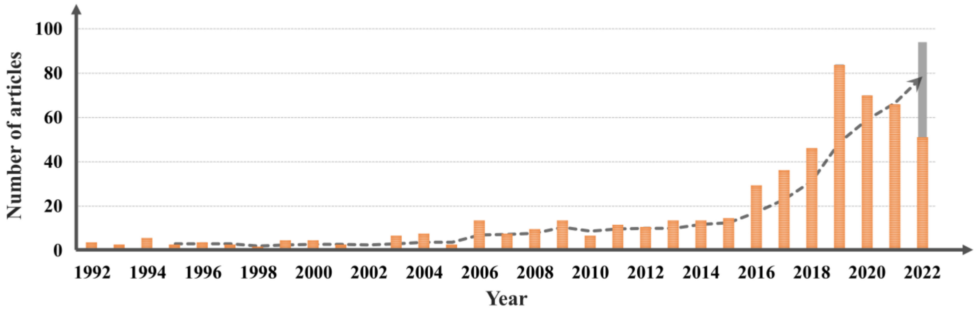

Figure 1. Statistical chart of related literature in 1992–2022.

2.1. Related Literature Analysis

Citespace software is selected for this section to analyze the above 539 pieces of literature for co-citation and co-keyword analysis. The analysis parameters are as follows: Nodetype for keywords and references, g-hex for 20, Pruning module with the options of 'Pathfinder', 'Pruning sliced network', and 'Pruning the merged network'. The analysis results area is shown in Figure 2.

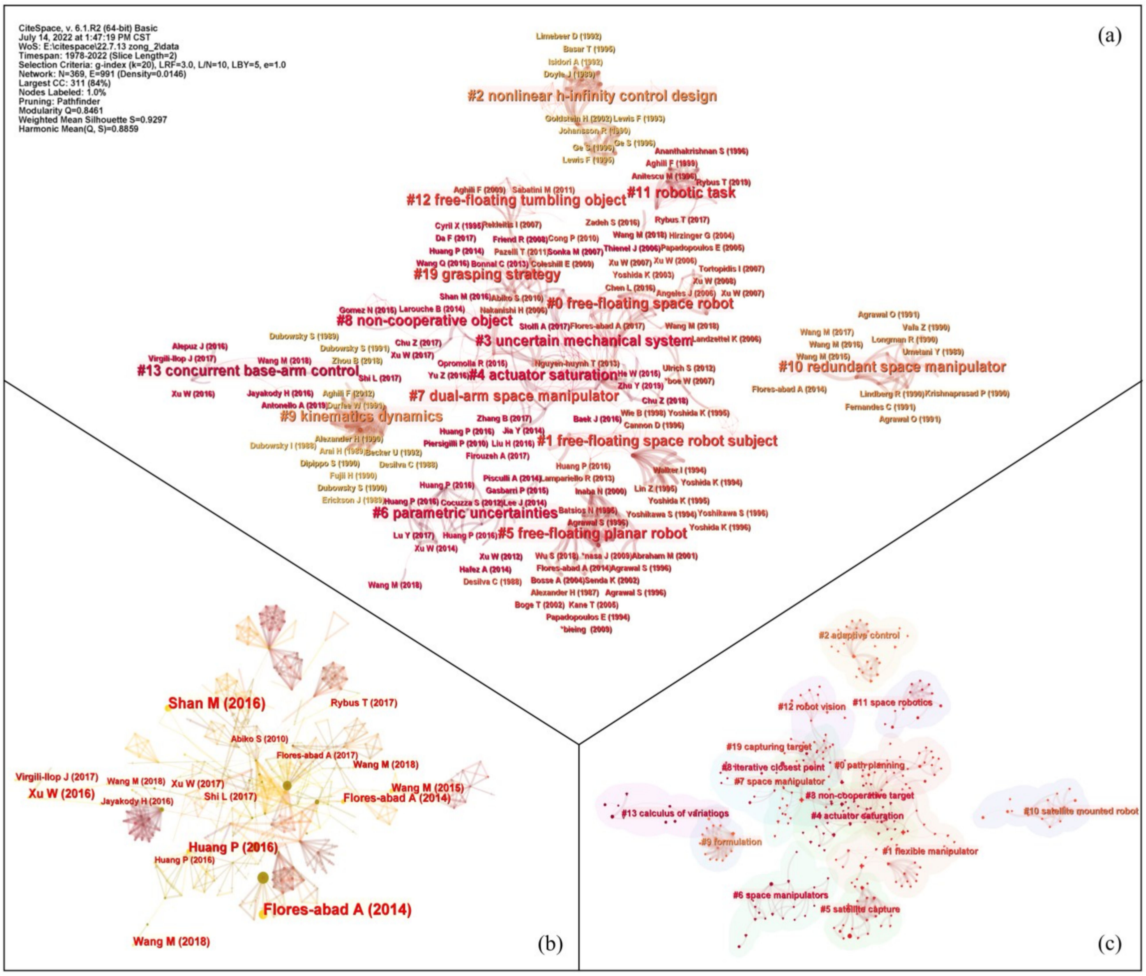

Figure 2. Citespace analysis results with parts: (**a**) co-word of title; (**b**) co-cited author; (**c**) keyword clustering.

According to the title co-word analysis results in Figure 2a, research objects in the RA-ADCR field are generally space manipulators with free-floating (#1, #5), dual-arm (#7), or redundant (#10) configurations. The captured target is typically a non-cooperative object (#8). Meanwhile, solving the parameter uncertainty problem (#6) in the base-robot arm parallel control (#13) has become a hotspot of research. Based on the co-referred authors' analysis results in Figure 2b, Flores, Xu, Huang, Wang, Shi, and others have achieved outstanding results. In addition, the field includes path planning (#0), adaptive control (#2), capture strategy (#8, #19), nonlinear numerical analysis (#9, #13), robot vision (#12), and many other subdivisions based on the keyword co-word clustering analysis in Figure 2c.

2.2. Historical Progres Periods

With 2019 as the dividing year, this section divides the research results in the field of RA-ADCR from 1983 to 2018 into three phases: the exploratory period, supplementary period, and developmental period. A detailed description of developmental transformations will follow in phases. The conventional RA-ADCR physical configuration consists of a base and one or more robotic arms. The base usually involves thrusters, reaction/momentum wheels, momentum control gyroscopes, or variable speed control moment gyroscopes for attitude control. During the mission execution, there is a dynamic coupling between the robot arm and the base of the microsatellite. The robot arm's movement will affect the satellite's attitude and position. In this case, the rotational inertia of the robot arm cannot be ignored. Moreover, the alteration in the satellite's attitude will seriously affect the communication effect and the working efficiency of the solar sail.

During the theoretical exploration period, researchers mainly discussed the control methods of the spacecraft, constructed kinematic/dynamical models based on different control methods, and carried out trajectory planning studies during the pre-capture process. Then, researchers complemented the mission's whole process during the theoretical supplement period. The advantages and weaknesses of different space robotic arm configurations are discussed and analyzed. The focus of the research began to diverge during the theory development period. Some researchers investigated methods for capturing targets with uncertain parameters or excessive rotation speed. However, other researchers focused on control methods that minimize the robotic arm's forces transmitted to the spacecraft.

2.2.1. 1983–1998 Theoretical Exploration Period

Initially, researchers transformed the RA-ADCR problem into a precision docking problem for rotating targets. They considered the spacecraft and the robotic arm as the two systems. In this case, the robotic arm executes the mission, and the base maintains the position and attitude of the spacecraft by counteracting the disturbances through the propulsion jets generated by thrusters [17]. The above was also an initial idea for the spacecraft free-flying model. The operation of such spacecraft is complex and requires high control accuracy of the robotic arm. Therefore, research during the theoretical exploration period focused on teleoperation, sensor design, and trajectory planning [18].

For the free-flying control model, the base consumes a tremendous amount of fuel to maintain its position and attitude, significantly reducing the service satellite's lifetime. Vafa [19] proposed a virtual manipulator method to construct an equivalent model of the space robotic arm. In addition, he also proposed a partial free-floating control model that converts the spherical hinge into a revolute pair to simplify the operation. This partial free-floating model only needs to maintain the spacecraft attitude, which reduces fuel consumption. To further reduce the energy loss, researchers presented a free-floating model in which the base does not provide external forces. This method follows the conservation of linear and angular momentum and considers the initial momentum to be zero [20–22]. However, the momentum of such free-floating spacecraft tends to accumulate and needs to be offset by fuel consumption due to the small environmental collisional perturbations or the deviation of attitude control [23]. Therefore, some researchers have also named the partial free-floating model combined with the free-floating model [24]. Such free-floating models have become the dominant control model for spacecraft given that they incur little or no extra fuel consumption.

Subsequently, researchers have focused on the construction of kinematic/dynamical models and trajectory planning for capture. Papadopoulos and Moosavian proposed the barycentric vectors method [25–27] and the direct path method [28] to construct kinematic and dynamical models for free-floating spacecraft. The direct path method uses the generalized Jacobi matrix, which is easier to implement than the center vector method [29]. Liang [30] proposed the dynamically equivalent manipulator method to preserve the dynamics of a free-floating robotic arm when mapped to a fixed-base robotic arm. Luo [31] first investigated the capture of cooperatively tumbling target objects. He designed a sensing feedback control law to ensure that the manipulator's position and orientation are asymptotically consistent with the tumbling object. Dubowsky [32] developed the concept of a disturbance map (DM) [19] and proposed the concept of an enhanced disturbance map (EDM) to reduce spacecraft disturbances. Compared to the prior trajectory planning methods, EDM breaks away from the DM method, which is only applicable to two-link planar robotic arm systems.

2.2.2. 1992–2007 Theoretical Supplement Period

During the theoretical supplement period, researchers explored the mission's whole process. Related research included motion estimation, kinetic model identification, velocity analysis at the moment of capture, and de-tumbling after capture. In 1992, Yoshida [33] took the captured moment as the node and divided the RA-ADCR task into three phases: pursuit, catch–grasp, and relieve–suppress. He initially applied the momentum conservation principle of point masses to the contact moment, which investigated the relationship between spacecraft and target motion. Matunaga [34] researched rapidly tumbling targets. At this point, direct capture was impossible. Therefore, he proposed a scheme using a buffered damper to absorb the rotational motion of the target satellite. Research on post-capture de-tumbling methods is relatively recent. In 2004, Dimitrov [35] introduced two post-capture control laws and named them distributed momentum control (DMC) and reaction null space control (RNSC). The DMC utilizes the conservation of the angular momentum of the system and aims to compensate for the remaining angular momentum of the system after the target is captured utilizing the reaction wheel. RNSC is mainly used in the post-capture stabilization phase to minimize the joint velocity based on keeping the base attitude constant. In 2007, Rekleitis [36] completed a simulation of target capture by dual-arm under transatlantic communication conditions based on prior knowledge and experience. However, all the targets of the studies above are cooperative. The targets' motion form and the kinematic and dynamic parameters are assumed to be known.

In 2004–2005, Lichter [37,38] implemented the motion estimation and kinetic model parameter identification method for unknown targets via in-orbit cameras. This approach complemented the limitation of RA-ADCR in the field of parameter identification and motivated researchers to explore the uncertainties of the target during the theoretical development period.

2.2.3. 2004–2018 Theoretical Development Period

In the theoretical development period, the uncertainties of the target and the minimization force on the base became the new research hotspots. The research also extended from a single rigid arm to different robot arm configurations, such as rigid–flexible coupled, redundancy, and dual-arm configurations [39]. Among them, the rigid–flexible coupled configuration helps to reduce the impact of capture on the target and spacecraft [40]. The redundant robotic arm configuration can reduce the torque transferred to the base while tracking the intended trajectory [41–43]. Moreover, the dual-arm configuration could counteract the positional interference by setting the balance arm [44]. In addition, it can also form an effective envelope area during capture to prevent the escape of a tumbling target [45].

Rapidly tumbling targets have been the subject of numerous research articles in terms of targets. The capture of rapidly tumbling targets is the intersection direction of the fields of space proximity operations and visual navigation and image processing techniques. Aiming at the recognition and determination of a target's position and shape, researchers have proposed two observation methods: active vision [46,47] and passive vision [48].

Responding to the excessive velocities and parameter uncertainties of tumbling targets, JAXA [49,50] first proposed using a flexible brush contactor for target pre-processing. Ma [51] divided the pre-capture into two stages: maintaining the spacecraft at the same rotation and linear velocity as the target and subsequently capturing the target with relative stationery. Aghili [52] used a Kalman filter to obtain target dynamics parameters from the on-orbit camera and initially applied them in the pre-capture and post-capture phases. Afterward, Aghili investigated the non-cooperative object minimum time de-tumbling [53] and the multi-arm cooperative trajectory planning [54]. Reiter [55] completed the minimum time implementation of joint space trajectory tracking based on the above.

Aiming to minimize the force on the base during the mission execution, Yoshida [56] introduced the combined inertia and Jacobian matrix to realize his concept of reaction null space in 1992. Notably, the zero reaction maneuver (ZRM) method has been validated on the ETS-VII satellite [57]. The above implementation uses a motion control strategy called sequential control. This method first achieves the target approach through base movement and then deploys the manipulator using the ZRM. Xu [58] proposed a new adaptive ZRM method that extends into the case of uncertainties in kinematic and dynamical parameters. Abiiko [59] applied impedance control theory to target de-tumbling and treated parameter uncertainty as a disturbance in control. Giordano [60] proposed a method of moment feedback to counteract the Coriolis and centrifugal forces generated by the robotic arm's motion.

Different from the above sequential motion control strategy, Sabatini [61] proposed a coordinated control method and verified the advantages of the combination of the base's attitude and the motion of arms through the air-bearing free-floating platform.

2.3. Recent Research Trends

In recent research, uncertainties have become the focus of extensive discussion among researchers in the field of RA-ADCR. The uncertainties referred to here hold the same interpretable range as the parameter uncertainties (Figure 2a, #6) mentioned in Citespace. Uncertainties include three aspects: unknown, dynamic change, and error. Among them, the unknown mainly refers to the non-structural orbital environment. The dynamic variation is reflected in both the target's kinematic parameters and the robot arm's structural parameters. The kinematic parameters of the target will change dramatically during the de-turning phase. In addition, the robotic arm's structural parameters keep changing dynamically during the task execution due to fuel consumption and joint movements. The last part of the uncertainty concentrates on the feedback and output errors triggered by the observers and actuators.

For the solution of parameter uncertainty problems, two different ways to address them are summarized based on recent studies. On the one hand, researchers would like to improve the discrimination accuracy and scope by constructing more accurate models to reduce the impact of systematic uncertainties. On the other hand, researchers have accepted the existence of such uncertainties. They attempted free/weak model approaches, end-effector designs, and robust controllers to improve error margins. As a result, the effects caused by uncertainties can be offset or circumvented.

The following two sections will focus on the research trends above, as shown in Figure 3. Both of them summarized the relevant research progress in the task execution flow. Based on different uncertainty handling methods, research results with different convergences will have significant discrepancies in the system modeling, mission planning and design, and implementation of RA-ADCR tasks.

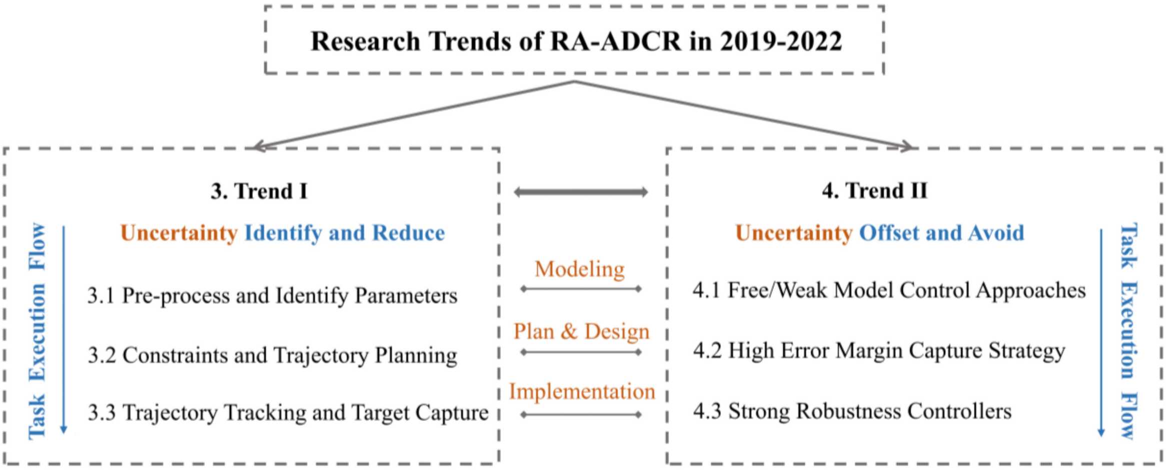

Figure 3. Research trends of RA-ADCR in 2019–2022.

3. Trend I: Uncertainty Identify and Reduce

Parameter uncertainties of the target and spacecraft are the primary source of systematic uncertainties and the main problem solved by RA-ADCR technology. Researchers have carried out extensive parameter identification work to improve the modeling accuracy. Then, model-based trajectory planning and tracking methods can be used to achieve capture. This section summarizes the research outcomes based on the identification and reduction trend of such parameter uncertainties.

The structure is sequenced with the task execution flow. In the system modeling phase, researchers first tried to stabilize the target in complex motion within an acceptable rotation range by pre-processing. Subsequently, parameter identification methods under both the pre-capture and post-capture phases are discussed, which will ensure more accurate system model construction.

In the mission planning stage, based on the research results in recent years, Section 3.2 summarizes the constraints and optimization conditions for the space robotic arm in trajectory planning after accurate model construction. In addition, trajectory planning methods are classified into offline trajectory planning and online trajectory planning according to the real-time effect. In general, offline trajectory planning methods are static and not particularly robust. Online trajectory planning methods are highly positively correlated with the ability of environment perception, which requires considerable computing power on satellites.

In fact, after reducing uncertainty and establishing an accurate system model, task execution will still be affected by other factors. Section 3.3 analyzes these influencing factors and summarizes ways to avoid these effects. Among the above, the first part expands on the accurate construction of the model, while the rest provides an overview of the model-based methods. It is worth noting that the trajectory planning and implementation methods discussed in Sections 3.2 and 3.3 are based on modeling methods with uncertainty identification and reduction tendencies.

3.1. Pre-Process and Identify Parameters

The target in a capture mission typically tumbles due to residual angular momentum. In addition, debris motion becomes more complicated by gravity, vortex damping, and flexible attachments [62,63] and generally includes both rotation and nutation [64]. When the capture target tumbles too quickly or is overly complex, direct capture using the robotic arm is extremely difficult. Therefore, it is necessary to stabilize the target within an acceptable rotation range during the pre-capture phase. The flexible pre-processing method using flexible rods and brushes is the most efficient [65], as shown in Figure 4.

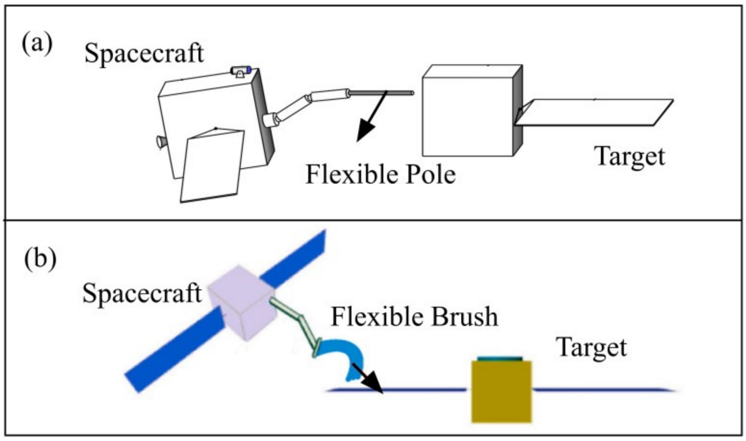

Figure 4. Pre-processing of tumbling target with parts: (**a**) flexible rod [63]; (**b**) flexible brush [66].

Flexible rods have five degrees of freedom for control, making it easier to obtain precise contact points. However, the control accuracy requirement of flexible rods needs to be increased. Researchers continuously refined a two-stage tumbling target pre-processing scheme based on flexible rods [65]. The first stage used a flexible impact to synchronize the angular velocity reduction method of the target in all three axes [62,63]. In the second stage, researchers used a collision recognition method to determine all inertial parameters using visual and moment sensors by using a force of less than 10 N [67]. Research on flexible brushes has focused on the control of the contact strategy [68], position [66], and force [69]. The dual-arm configuration is likely to be a popular configuration for flexible brush de-tumbling. The dual-arm robotic arm has a counterbalance arm to offset the base's disturbance caused by the friction between the flexible brush and the target. In addition, such a robotic arm can develop an effective envelope region for relatively stationary target objects, which improves the capture success rate and enables direct capture. Table 1 compares the differences and effectiveness of the flexible rod and flexible brush.

Table 1. Pro-processing of flexible rod and brush.

-	Mode of Action	Contact Mode
Flexible rod (a)	Impact	Two-stage instantaneous
Flexible brush (b)	Friction	Multiple persistent

When the rotation of the target is in an acceptable range, using parameter identification methods to reduce uncertainty becomes a critical element of the study. In the RA-ADCR mission procedures, there are three objects for parameter identification: spacecraft, tumbling targets, and combinations. In the pre-capture phase, researchers need to carry out the identification of the first two parameters. As physical models of spacecraft and capture targets are known to different degrees, their parameters differ in obtaining methods. The physical model of the spacecraft is known. Its parameters change mainly due to motion operations and fuel consumption. Therefore, model-based algorithms are suitable for this case. Researchers have proposed methods based on equations of motion [70] and momentum conservation [71,72] for parameter identification of spacecraft. Momentum-conservation-based methods have become a hot research topic because the observation of acceleration is avoidable compared with motion equation-based methods.

The characteristics of objects in long-term orbit are inherently difficult to assess, especially for space debris that has suffered an explosion [73]. Model-based parameter identification methods are not applicable. In addition, parameters such as the rotational inertia of a rotating target depend on factors such as the exact location of the capture point. Therefore, target parameters will only be able to be obtained by estimation [73]. Currently, there are two kinds of solutions. One is filtering and smoothing algorithms. Researchers have extensively discussed filtering methods such as the extended Kalman filter [74,75], unscented Kalman filter [76], particle filter [77], and minimum energy filter [78]. The other uses SLAM algorithms to solve the non-cooperative target's state estimation [79,80]. After the manipulator captures the tumbling target, the parameter identification of the combination can help achieve the target's de-tumbling. However, it is worth noting that there is relative sliding between the target and the spacecraft, which becomes the main difficulty in modeling. Researchers used learning algorithms to achieve parameter discrimination by parallelizing past motion data points with transient motion data points [81]. Subsequent studies have improved the scaling factor, which improved the convergence [82]. On the other hand, researchers have improved the method by constructing an extended observer for the parametric explicit linear time-varying model [83]. This method effectively estimates the inertial parameters in dynamic variation.

In recent years, research development trends have varied for different parameters. In the pre-capture phase, the research focuses on reducing the need for computing power and result improvements. In terms of reducing on-satellite computing power, relaxing the persistent excitation (PE) condition and using the interval excitation (IE) condition for parameter identification has become a hot topic [72,74,84]. In addition, task priority-based filtering estimation strategies are also helpful for reducing the arithmetic power on satellites [75]. To improve the results, researchers have attempted to fuse different filtering methods, including a hybrid Kalman filter [76] and a two-stage filter [85]. Those filters help to improve the accuracy and stability of the outputs. On the other hand, for the cumulative error that occurs after filtering, the researchers used a closed-loop detection method for reduction [86]. After the robotic arm completes the capture, the PE condition is necessary to avoid collisions between the spacecraft and the target. Therefore, model construction and the real-time improvement of identification are the focus of this research. On the one hand, researchers proposed momentum-based and force-based identification equations based on the combination [87,88]. Compared to conventional methods, momentum-based equations can estimate all inertial parameters simultaneously in one step, and force-based equations have no requirement on the joint moments. On the other hand, researchers continued Na's work [89] to obtain estimation error expressions using multiple filtering operations. In addition, the application of the terminal sliding mode achieves convergence of the parameter identification in finite time [90].

3.2. Constraints and Trajectory Planning

In addition to obstacle avoidance, output limits, singularity, maximum joint torque, maximum joint acceleration, and maximum base force are also constraints of trajectory planning [91,92]. The output limitation represents that the actuators must be kept within the pre-defined constraints to avoid unexpected collisions. Moreover, the minimum base perturbation, time, and fuel consumption are the direction of trajectory planning optimization, which helps to increase the system's service life [93–95]. As shown in Figure 5, there are two ideas to handle the trajectory planning problem. One is the offline trajectory planning method, which only focuses on the initial and final attitude of the base. The other is the online trajectory planning method, which needs to keep the base attitude stable during the whole motion.

Offline trajectory planning includes both heuristic algorithms and nonlinear optimization methods. Heuristic offline trajectory planning methods include the rapid-exploring random trees algorithm (RRT) [96], enhanced bidirectional approach (EBA) [97], multi-objective particle swarm optimization algorithm (MOPSO) [98,99], and improved genetic algorithm [100]. On the other hand, researchers transform planning problems into nonlinear optimization problems and solve them by variational methods [101] and active sets [102,103]. Among them, the RRT algorithm is intuitive for trajectory planning [96]. The EBA method solves trajectory planning by modeling as a kind of error convergence problem by presetting the initial and final configurations of the robot arm. This method is computationally efficient and easy to implement on satellites. However, the MOPSO algorithm requires the establishment of a cost function. This method transforms the trajectory planning problem into a multi-objective optimization problem [104]. Compared with heuristic algorithms, the method of nonlinear optimization is reproducible and easy to falsify in implementation.

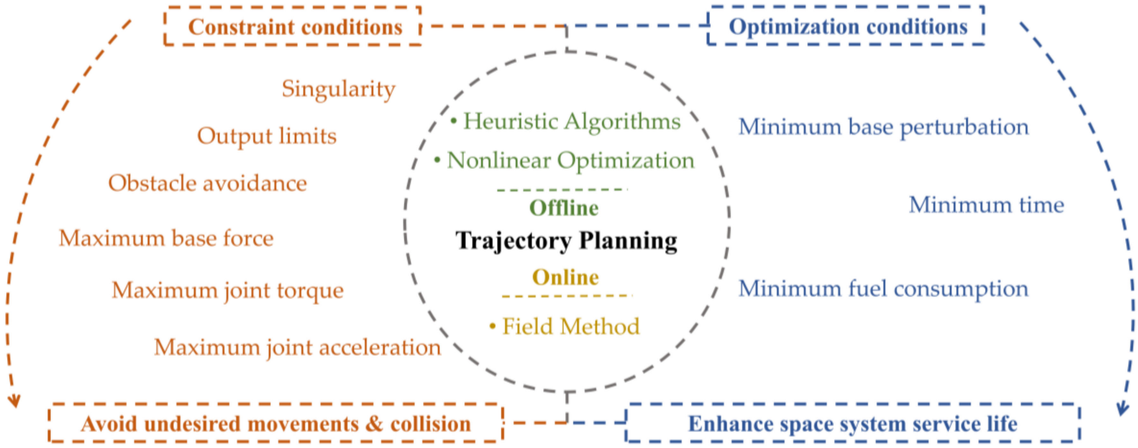

Figure 5. Conditions and methods of trajectory planning.

However, it is worth noting that the offline trajectory planning method is static and not particularly robust. This implies that the trajectory has to be recomputed and regenerated when the target or obstacle changes. Xie [105] fused RRT with forward and backward reaching inverse kinematics to avoid inverse kinematics solutions. This method improves the efficiency of trajectory planning by reducing the need for on-satellite computing power. Zhang [106] proposed a two-level local planner based on the RRT algorithm, the former ensuring efficient exploration of the configuration and the latter ensuring fast algorithm convergence with singularity avoidance. This approach accomplishes task planning without solving the inverse kinematic problem and preserves the attitude constraint. In addition, researchers attempted to improve the MOPSO algorithm performance with chaotic particles [107] and penalty factors [108]. The former improves the precision phenomenon, while the latter balances the penalty and search ability under multiple constraints. There is also research that integrates the MOPSO algorithm with collision detection techniques. This method guides obstacle avoidance trajectory planning by calculating the distance between the obstacle and each joint in real time [109].

Online trajectory planning is mainly realized by field methods such as artificial potential field (APF), obstacle vector field (OVF), and acceleration potential field (AccPF), which can dynamically adjust according to conditional changes. In the pre-capture phase, Rybus compared RRT, APF, and OVF trajectory planning algorithms. The results show that the OVF is superior to APF, and the time required to solve is shorter than APF and RRT [110]. In the post-capture phase, Zhan [111,112] used the AccPF method to construct attractive and repulsive potential fields to achieve trajectory planning. The former field is used for momentum removal, and the latter is used for obstacle avoidance. In addition, some studies innovatively integrated the APF with reinforcement learning (RL) to realize the trajectory planning of a dual-arm or redundant manipulator. This method is applicable to the case of relative motion between the target and satellite [113,114]. However, planning effectiveness within field methods is highly positively correlated with environmental perception ability. This implies that excellent planning results require that the service satellites consume more on-satellite computing power for accurate field construction.

3.3. Trajectory Tracking and Target Capture

In addition to uncertainty, external perturbations, input nonlinearities, and elastic vibrations also exist in trajectory tracking. There exist two types of input nonlinearity. One is input saturation, mainly caused by the actuator's physical limitations. The other is input dead zones, primarily driven by actuator defects, such as backlash, hysteresis, and friction [115]. Two methods exist for addressing the above effects. One is the model prediction method, in which the system dynamics model [116,117] or error dynamics model [118] is built by feedback. The main approaches include the visual servo [119–121], probabilistic ensemble neural network [116,117], and long-short-term memory network method [122,123]. The above-mentioned studies emphasize the performance of long-term predictions and sensitivity to hyperparameters. Another approach introduces an unknown integration term, which can be observed by constructing an adaptive interference observer based on a neural network [124–126] or a kind of sliding mode [127,128].

Force estimation and control become primary research when space robotic arms use impedance control to achieve the target's de-tumbling. Flexible configurations have received much attention because of the minor impact of collisions. Flexible components will suffer from deformation and increased joint friction during task execution. Establishing the dynamics equations for flexible rods and joints is necessary [129,130]. In the post-capture phase, the friction between the end of the manipulator and the target needs precise impedance control. The constant damping impedance controller based on force [69], position [40,131], or hybrid [69,132] makes the end of the robot arm behave as a mass-spring-damping system to absorb the impact energy. In addition, reducing the contact force during the collision by setting a proper force constraint function can decrease the motion overshoot and stabilization time [133]. However, the high stiffness required by the robotic arm for pre-capture motion control and the flexibility required for soft target capture is antagonistic and contradictory. The active compliance controller has the advantage of balancing such a contradictory relationship [134]. Nevertheless, the parameters of the active compliance controller need to be optimally tuned to obtain a better control effect. Researchers have used RL [135], PSO [136], and other methods to adaptively adjust parameters. The above methods slow the impact suffered by the target when it comes into contact with the robot arm and prolong the collision time to avoid sudden velocity changes [137,138].

4. Trend II: Uncertainty Offset and Avoid

Apart from reducing uncertainties through parameter identification, researchers accept the existence of such uncertainties and shift their focus from reducing uncertainties to offsetting and avoiding the effects of uncertainties. This means that in this research tendency, improvement of the error margin will replace accurate model construction as the research priority.

Corresponding to the structure of the previous section, this section will also be ordered by task execution flow. In the system modeling phase, researchers have tried using a free/weak model approach to avoid precise model construction. Different from model control based on kinematics and dynamics, researchers choose data-based or reinforcement learning methods to achieve the same control effect.

In the mission planning and design phase, a proper strategy will help to improve the error margin, which will greatly benefit the capture of the target. When the target is reserved for capture location, the target point used in trajectory planning (Section 3.2) can be expanded into multiple or single regions, which will result in an appreciable error margin. The target exists in the case of no feature capture point. At this time, the capturing strategy will shift to the design of actuators. Section 4.2 classifies these specially designed actuators: reciprocally bonded, internally caged, and externally folded actuators.

In the implementation phase, the researchers endow the controller with sufficient robustness to enable the robotic arm to track the trajectory despite uncertainty, external disturbances, input saturation, etc. The use of strong robustness controllers will also effectively reduce the chattering at the end of the robot arm. The current research hotspot is the modification of the sliding mode controller to improve the control accuracy based on achieving the above task requirements.

4.1. Free/Weak Model Control Approaches

Aiming to avoid complicated parameter identification, researchers proposed a series of model-free/weak-model solutions. There are two kinds of implementation schemes. One used a data-based control scheme for robotic arms, which is based on the free/weak model and can directly control manipulators based on the obtained data [139]. The other used RL to train the system to ensure stable operation under such model-free conditions [140].

Researchers classified manipulator control methods into three categories: dynamics-based, kinematics-based, and data-based [141]. Among them, the first two are model control methods. Parameter identification work is required to construct accurate kinematic and dynamic models. Data-based control methods are generally free/weak model-based. Typical schemes include iterative learning control (ILC) [142], virtual reference feedback tuning (VRFT) [143], and forecasting-based data-driven model-free adaptive sliding mode attitude control [144]. Among them, ILC proposes a robust control allocation strategy to compensate for the possible observation errors of iterative observers in real time. VRFT ensures that controllers learn from few input–output data and collect more input–state data during dynamic compensation. In addition, Liu [145] transformed the trajectory tracking problem into a regulation problem with an argument system and iterated the measurement data using the Q-learning algorithm. Subsequently, model-free control is performed by solving the bellman optimal equation.

The hierarchical decoupling optimization-reinforcement learning strategy has become a recent research hotspot in implementing model-free control. At present, there are two approaches to spacecraft system division. Based on the system's physical configuration, the spacecraft system was divided into two subsystems: fast and slow. The slow subsystem consists of a base, rigid joint motion, and flexible rod vibration, which uses model-free control methods such as reinforcement learning and virtual reference feedback coordination [146,147]. The other was task-based and divided the system into two layers: high and low. The high-level strategy is trajectory planning, while the low-level strategy decomposes the trajectory tracking task into position and orientation reinforcement learning subsystems. The stable convergence of the system was ensured by introducing the event-based alternating optimization method [148].

4.2. High Error Margin Capture Strategy

When the mission target of RA-ADCR is the defunct satellite or rocket launch stage, the capture point is generally non-unique. Dynamic closest point capture [149] and area-oriented capture [150] can improve capture efficiency for such cases. The former expands the previously fixed capture points to DCPs, which provides more points for capture. The latter expands the tracked capture object from a single point to a region to obtain a more considerable positional error margin for dual-arm spacecraft. In addition, the method with clamping at both ends can also stabilize and de-tumble the target object [151,152]. Except for specific targets, the RA-ADCR mission probably contains targets without feature capture points. In this case, it is difficult for the end-effector with two-finger or three-finger configurations to meet the mission requirements. Therefore, the researchers embarked on structural design work for the end-effector. The designed end-effector improves the capture error margin and reduces the accuracy requirements. On the other hand, the end-effector with a passive compliance design also has the effect of preventing escape, relieving shock, and reducing chattering. There are three types of end-effectors for RA-ADCR tasks: reciprocally bonded, internally caged, and externally folded.

In the design of reciprocally bonded structures, researchers imitated geckos and proposed using the Lorentz force to capture the target [153], as shown in Figure 6a [154]. Zhang [155] proposed a new bonding capture mechanism as shown in Figure 6b. Moreover, a contact detection algorithm considering bonding failure was proposed. Such bonded end-effectors have no bearing on the size of the space debris and are the simplest to capture. However, it is worth noting that after bonding the spacecraft to the target, the impact force and moment will transmit instantaneously. Such actuators require a high structural strength to avoid fracture due to impact.

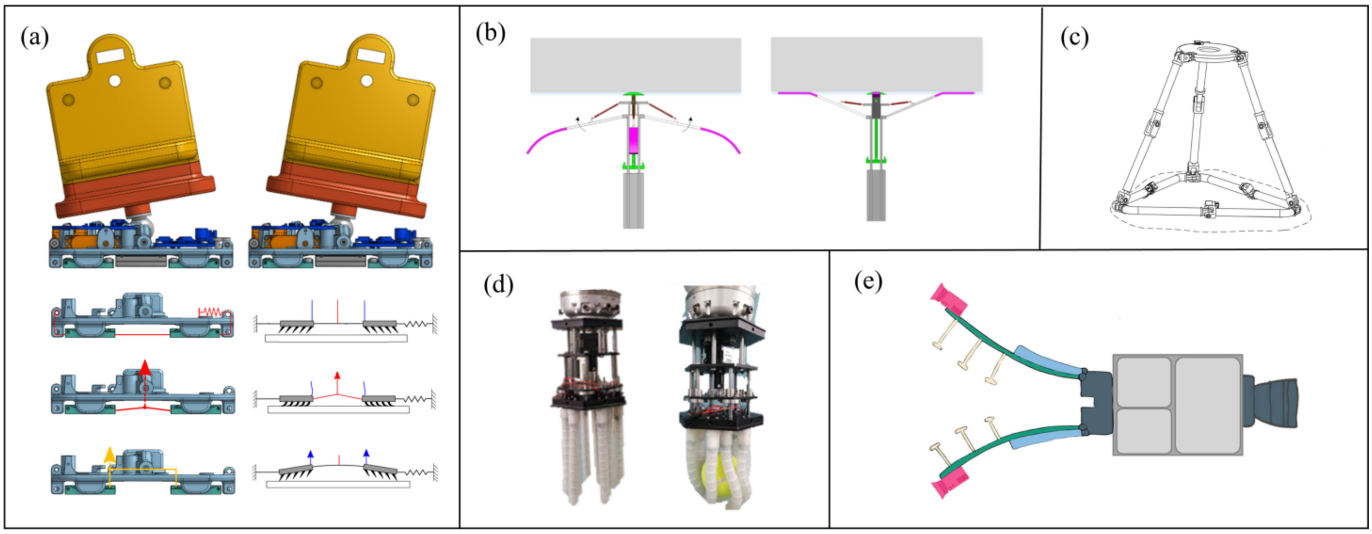

Figure 6. Reciprocally bonded/internally caged end-effector with parts: (**a**) gecko-like reciprocally bonded end-effector [154]; (**b**) bonding capture mechanism [155]; (**c**) multi-closed-loop flexible actuators [156]; (**d**) sea-anemone-like multi-flexible arm [157]; (**e**) flycatcher-like internally caged end-effector [158].

The internally caged structures construct a closed deformable cage for capturing and de-tumbling targets by changing the shape. To avoid undesired rigid shocks, the actuators of spacecraft are generally flexible, as shown in Figure 6c–e. There are two forms of structural design, multi-closed-loop and bionic. As shown in Figure 6c, the design of multi-closed-loop flexible actuators provides complete locking with the target by revolute pairs [156]. For the design of bionic structures, researchers designed several end-effectors inspired by the sea anemone (Figure 6d) [157] and flycatcher (Figure 6e) [158]. This method of capturing has low error accuracy requirements for position and orientation, and space debris is less likely to escape after the completion of capture. However, there are limitations on the size of space debris and a high probability of space debris escaping during the pre-capture phase. In addition, internally caged structures will inevitably encounter unforeseen collisions with space debris. Extensive ground experiments to verify the feasibility are necessary.

The externally folded end effectors are the primary field for the design of capture actuators. Both closed and enveloped configurations exist. The typical capture flow of the closed configuration is shown in Figure 7a [159]. The primary purpose of the closed configuration is similar to that of the internally caged actuators, which transport the space debris into the enclosed cage to achieve target capture and de-tumbling. However, the difference is that such externally folded end effectors have a more extensive capture range at the expense of variability in the enclosed caged one. Sun [160] proposed an externally folded capture device based on the origami principle, which received wide attention, as shown in Figure 7b. The numbers in subfigure (b) imply the relationships among the components of such capture device. On the other hand, the envelope-based externally folded actuators emulate the capture form of the dual-arm. Researchers proposed the deployable grasping mechanism, a deployable robotic arm device based on a tandem of metamorphic mechanism modules (MMMs), as shown in Figure 7c [161]. However, the above MMMs are dynamically coupled. The capture operation cannot be executed until it is fully expanded. Therefore, the research focused on motion decoupling [162] and envelope reliability [163]. In response to the asymmetry that occurred in MMMs, Li [164] proposed basic deployable modules. Basic deployable modules consist of both a scissor mechanism and two parallelogram mechanisms, as shown in Figure 7d.

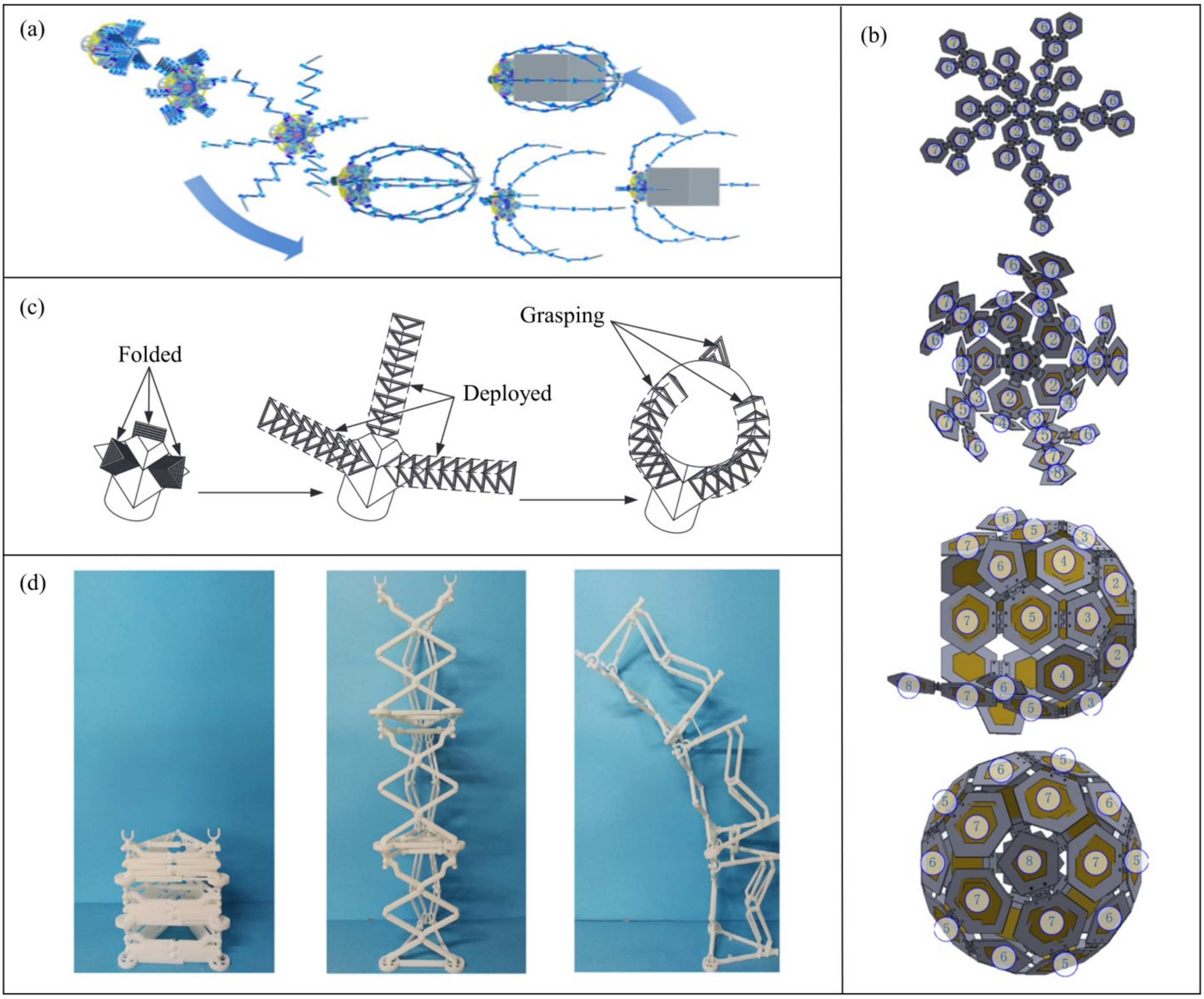

Figure 7. Externally folded end-effector: (**a**) the typical capture flow of closed configuration [159]; (**b**) externally folded capture device based on the origami principle [160]; (**c**) deployable grasping mechanism [161]; (**d**) basic deployable modules [164].

The externally folded configuration has many advantages in terms of implementation compared to the other two configurations. First, it has a larger capture range and more cushioned structures. In addition, it allows the target to rotate on a specific axis during capturing. However, the noteworthy point is that the target's prior physical model information is necessary for designing such actuators. Conversely, the space debris volume does not affect the externally bonded actuator. Moreover, the internally caged actuator is bounded by the maximum volume only.

Currently, the externally gathered end-effector has been demonstrated in several projects under development. In 2018, the Japan Aerospace Exploration Agency [11,165] combined the method of manipulator capture and tether capture and developed a space debris micro-remover (SDMR), as shown in Figure 8a. It consists of an extensible folder flexible arm and an electrodynamic tether [165]. The flexible robotic arm forms a broad externally folded actuator for space debris capture. The electrodynamic tether generates

Lorentz forces with the geomagnetic field to de-orbit space debris in low Earth orbit. ESA also researched the Clearspace-One mission, which loads four DEMES arms, as shown in Figure 8b. The real-life "Pac-Man" provides a greater maneuvering margin and high fault tolerance for multiple capture operations [166] and is expected to be launched in 2026. The mission target is the Vespa upper stage with a mass of 112 kg and an orbital altitude of 664–801 km. However, there are two significant challenges. The first is that the Vespa may have disintegrated with more than one piece of debris. The other is that the data must be analyzed on the satellite to meet navigation needs [54,167]. In 2020, Singh and Moojj [168,169] continued the research based on the ESA' e. Deorbit mission, which aims to de-orbit the Envisat. Then, a combined vehicle including a robotic arm and tentacles was designed as shown in Figure 8c. The purpose of the tentacles is to capture the body of Envisat, and the role of the robotic arm is to capture the boom of the solar panel.

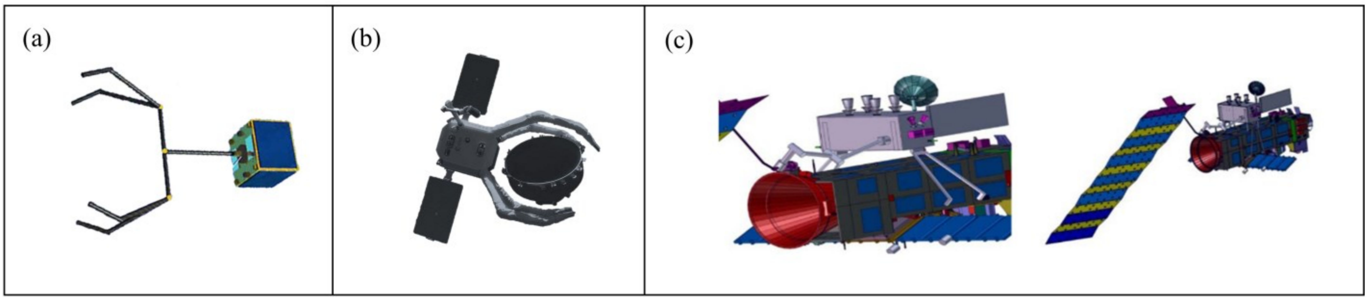

Figure 8. Project scheme: (**a**) space debris micro-remover, JAXA [165]; (**b**) "Pac-Man", Clearspace-1, ESA [167]; (**c**) e. Deorbit's follow-up research [168,169].

4.3. Strong Robustness Controllers

On the other hand, researchers have taken the perspective of controller design to assign sufficient robustness in controllers for solving the systems' problems of uncertainty, external disturbances, and input saturation. Such highly robust controllers enable the spacecraft to track the desired trajectory and effectively reduce chattering even when subjected to continuous disturbances. Due to its high adaptability, the sliding mode controller has become a hot research topic. In recent years, researchers have carried out numerous modifications and optimizations for the sliding mode controller. The research mainly focused on gradually improving the tracking accuracy based on solving the chattering and convergence problems. Two directions exist for sliding mode control optimization. One is the optimization of the structure of sliding mode control. Ensuring that the trajectory tracking task converges in finite time, researchers improved the sliding mode control by adding time-delay estimation [170–172] or non-singular terminal [173–175] to reduce chattering and improve transient performance. The other integrated different computational intelligence approaches to endow the sliding mode controller with higher adaptiveness. Researchers incorporated the fuzzy logic system [176], RL [177], adaptive dynamic programming [174,178], super-twisting algorithm [173], and other techniques with sliding mode control to improve the adaptivity and transient performance. In addition, positional feedback [175] and partial power feedback techniques [179] can also improve tracking accuracy.

In addition to the sliding mode controller, researchers have also conducted related studies on others. Seddaoui [180] designed an H_∞ controller in which the base has no need to maintain a particular attitude but tracks the desired trajectory. Gangapersaud [181] proposed a de-tumbling controller based on an uncertainty model for directly controlling the end-effector contact forces and moments. To reduce low-frequency chattering and improve tracking accuracy, Liu [182] proposed a minimum disturbance controller based on synchronous adaptive acceleration planning. Shi [183] proposed an optimized adaptive variable structure controller. This controller uses a modified Gaussian barebones differential evolution to shorten the stabilization time and improve the control accuracy, which is targeted for motion error.

5. Challenges and Reflections

Compared with other space missions, space debris removal missions suffer from high uncertainty, high mission difficulty, and multiple time-varying factors, which implies the need for both safety and real-time in RA-ADCR. In addition, it is worth noting that space debris removal missions themselves do not provide direct economic benefits. Constrained by the cost of revenue, the small satellite platform equipped with a robotic arm will be bounded by the on-satellite computing power, which will directly impact the effectiveness of mission execution.

The following are examples to support the above argument. Model-based control methods require accurate environmental, robotic arm, and target models. These methods generally have heavy on-satellite computing power requirements and thus need to operate offline. Space robotic systems are in a dynamically changing environment. The large time delay due to insufficient satellite arithmetic power will greatly increase the modeling error, which in turn will affect the system's security. Similarly, the space free/weak model control system needs additional on-satellite computing power to verify the feasibility of motion before execution. When the on-satellite arithmetic power is insufficient, the system will reduce the dimensions of verifying parameters to maintain its data-based control strategy, which will have a direct impact on the system's security. If safety cannot be guaranteed, it will be followed by collision and disintegration. The consequences will be irreversible.

This section analyzes such challenges as balancing on-satellite computing power limitations with task execution effectiveness based on the RA-ADCR task execution flow. In addition, feasible solutions for the current phase are discussed.

5.1. Observation and Model Building

The observation and parameter identification of a target is unavoidable in the RA-ADCR task mission. Researchers have proposed two observation methods for non-cooperative targets, the filter smoothing algorithm and the SLAM algorithm. However, it is worth noting that the former is subject to error accumulation and deviation from the actual value. The latter requires excessive on-satellite computing power and is thus not easy to implement in orbit. Researchers considered a closed-loop detection approach to reduce the errors of the former estimation method. However, this would sacrifice a large amount of computing power and affect real-time performance. The primary approach is to sacrifice the recognition accuracy in the pre-capture stage to improve the computational efficiency or reduce the computing power requirement. However, it is notable that the reduction in target recognition accuracy will affect the model construction, which requires the relaxation of the optimization conditions in trajectory planning. It is challenging for the RA-ADCR task to reduce the on-satellite computing power and improve the computational efficiency without sacrificing the accuracy of target identification.

Inspired by the model-free hierarchical decoupled reinforcement learning method, stratifying the target observations according to the degree of importance or the rate of dynamic change might be feasible. In this case, the high-level ones are essential and dynamically significant observations, which use the PE condition for continuous tracking. In contrast, the lower-level observations use the IE condition for result validation and correction.

5.2. Transformation and Trajectory Planning

Obstacle avoidance in trajectory planning often requires an accurate environment model. In general, trajectory planning includes both constraint conditions and optimization conditions. The constraint conditions mainly include environmental obstacle avoidance, output limitation, singularity avoidance, maximum torque, and maximum joint acceleration. The purpose of the above is to ensure controllability and safety. Optimization conditions consist of minimum base disturbance and minimum time. The purpose is to reduce the system's fuel consumption and improve the service life. When the constraints increase, heuristic algorithms such as RRT and PSO will accelerate the convergence. However, according to the discussion of offline trajectory planning methods in Section 3.2, this method cannot adapt to the dynamic environment. The trajectory generation speed requires an increase to reduce the impact. Therefore, adding optimization conditions reduces the trajectory generation rate, which is unsuitable for heuristic algorithms. The spacecraft system needs to sacrifice the satellite's lifetime for operational security. The field methods can dynamically adjust according to environmental changes, making it easier to achieve real-time trajectory planning than heuristic algorithms. However, unlike the heuristic algorithm, increasing constraints and optimization conditions will reduce the real-time capability of the field methods. In addition, the planning effectiveness of the above methods highly positively correlates with the ability of environmental perception. Superior planning results require the service satellites to consume more computing power for accurate construction of the field.

Online trajectory planning is more valuable in terms of implementation than offline trajectory planning. The following will focus on the optimization of field methods. The potential field-based trajectory planning method mainly guides the motion tendency of the manipulator. A semi-blind field planning method is proposed to reduce the on-satellite computing power. The spacecraft constructs the field model of the environment around the manipulator and considers the target as the only known point in the blind area. Subsequently, the initial tendency of the arms' motion is the line between the target point and the end-effector. The mission of obstacle avoidance turns into a topology-based joint motion planning mission by constructing the field from the base to the end-effector. Finally, the trajectory planning task is completed once the target point overlaps with the end-effector.

5.3. Tracking and Target Capture

Currently, there are two development trends for trajectory tracking and target capture. On the one hand, researchers improved model-controlled trajectory tracking accuracy by developing parameter identification and increasing observation feedback. The feasibility of this approach can be easily verified at the expense of onboard computing power. On the other hand, researchers expanded the capture points and designed end-effectors to offset the trajectory tracking errors. This approach avoids sacrificing a large amount of on-satellite computing power and is suitable for in-orbit implementation. However, neglecting the tracking error may lead to undesired failures, which leads to difficulty in feasibility verification. In cases of using end-effectors with unique configurations, the capture process is no longer relatively stationary. Additional design of the maneuvering process for capture is needed. In addition, the effect of the interaction of the end-effector with the target requires further theoretical exploration and validation.

Based on ensuring lightness and foldability, the design of the externally gathered end-effector becomes the central promise for achieving target capture. Such actuators are expected to hold vibration damping, friction de-tumbling, and target anti-escape strategies. However, using flexible rods and brushes for target pre-processing is the most feasible option based on the current state of the technology and mission feasibility requirements. This approach converts the non-cooperative target into a cooperative target, which helps to convert the RA-ADCR mission into a rendezvous and docking mission.

6. Future Outlook

This section provides a future outlook of the RA-ADCR field based on the research content. At the level of theoretical exploration, the use of simpler model construction methods will fundamentally solve the issue of on-satellite computing power. Regarding task implementation, identification reduction and offset avoidance are one and two sides to uncertainty treatment. The trend toward convergence may lead to the keynote in the future. Once the RA-ADCR task fails, the consequence is destructive. Therefore, building a feasibility validation platform for different schemes is necessary.

6.1. Convergence of Tendencies

There is no doubt that the processing of systematic uncertainty will be a significant research component in the RA-ADCR field for a long time. However, it is worth noting that the uncertainties will not be fully identified and eliminated in task realization. Similarly, the avoidance of uncertainties is never indefinite. Identification reduction and impact avoidance are two sides of the same coin, and the convergence tendency may be the mainstream for mission realization. At present, there is an initial indication of such a convergence tendency. In the pre-capture stage, trajectory planning and tracking require high accuracy of the target's position, state, and other information. Therefore, RA-ADCR technology with uncertainty identification and reduction tendency mainly concentrates on this phase. In contrast, research on uncertainty offset avoidance tendencies has mainly focused on capturing instant and post-capture phases. In the future, the reasonable characterization of the uncertainties in each process phase and the research integrating such two tendencies will become research hotspots.

6.2. Fundamental Modeling Theory

Recently, several studies have emerged to advance fundamental modeling theory. In the pre-capture phase, He et al. [184] proposed the Takagi-Sugeno (T-S) fuzzy descriptor approach to construct the model for kinematic and dynamic models. On the other hand, Zong et al. [185] flipped the space robotic arm system and considered the end-effector as a virtual base for kinematic modeling. Shao et al. [186] proposed an adaptive Radau Pseudospectral method to discretize the system dynamics. At the instant of capture, Zhang et al. [187] transformed the complex contact process into a virtual monolithic energy change and established a more general continuous contact model. In the post-capture phase, She et al. [188,189] proposed a method with additional degrees of freedom to efficiently describe the relative motion between the target and spacecraft. In addition, methods for computing generic contact dynamics were given. Stolfi et al. [190] developed a closed-loop multibody dynamics model consisting of a dual-arm manipulator with a non-cooperative target. As a prerequisite element of model control, the underlying modeling theory will be further developed to reduce arithmetic power and improve generality based on continuously increasing modeling accuracy.

6.3. Feasibility Verification Platform

Since the consequences of a failed space debris capture mission are unacceptable, guaranteeing a high success rate is the only way to apply the technology in practice. Currently, there is no relevant organization applying the RA-ADCR method to actual space debris capture due to its complexity and difficulty. However, robotic arm capture has the characteristics of high fault tolerance and multi-capturable compared with other forms. After the RA-ADCR methods become mature, the cost will be significantly lower than that of other forms. Low cost is undoubtedly the most attractive point for active debris removal missions in which the potential benefits are much greater than the direct benefits.

Considering the complexity of the space environment, it is unrealistic to identify all the systematic uncertainties to carry out fully confident model control. Therefore, the simulation platform for validation is essential. The ground test platforms focus on modeling the microgravity environment, which includes submerged neutrally buoyant simulators, drop towers, hardware-in-the-loop systems and parabolic flights. However, these systems are limited by joint friction, the spatial extent of the test, the duration of the test, and the recreation of microgravity [191].

Another possible approach is an air-bearing microgravity testbed. Both the base and the manipulators are air-bearing lifted to eliminate the gravity effect. Papadopoulos [192] designed the NTUA software simulator and the hardware emulator for space robots. Sabatini [193] created the PINOCCHIO simulator using a two-stage sequential control strategy. The U.S. Naval Postgraduate School [194,195] has developed a floating spacecraft simulator with a four-link serial manipulator that enables target approach, capture and de-tumbling based on different control strategies.

It is worth nothing that all of the above-mentioned test platforms use external vision, while the absolute position and attitude of the spacecraft are unknown in a real mission. Moreover, the description of the effects of other gravitational fields and tiny particle collisions in space on the system is not sufficient. In the future, researchers need to shift their research mindset from solving problems to validating methods.

7. Conclusions

In this paper, an in-depth investigation was conducted, and the RA-ADRC methods in recent years were discussed with the aim to promote their development. With 2019 as the time point, in this review, the research on prior years was gathered in three phases: theoretical exploration, complementarity, and development. In addition, the research in later years was discussed in terms of two trends: uncertainty identification reduction and offset avoidance. Subsequently, the challenges and feasible solutions for balancing on-satellite computing power limitations with task execution effectiveness were discussed. Finally, an outlook on the development direction toward convergence of uncertainty identification reduction and offset avoidance in the RA-ADCR field was presented. Moreover, the important role of fundamental modeling theories and feasibility verification platforms for the development of the field was emphasized.

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Nomenclature

AccPF	Acceleration potential field
APF	Artificial potential field
DM	Disturbance map
DMC	Distributed momentum control
EBA	Enhanced bidirectional approach
EDM	Enhanced disturbance map
IE	Interval excitation
ILC	Iterative learning control
MMMs	Metamorphic mechanism modules
MOPSO	Multi-objective particle swarm optimization algorithm
OVF	Obstacle vector field
PE	Persistent excitation
RA-ADCR	Robotic arm active debris capture removal
RL	Reinforcement learning
RNSC	Reaction null space control
RRT	Rapid-exploring random trees algorithm
SLAM	Simultaneous localization and mapping
VRFT	Virtual reference feedback tuning
ZRM	Zero reaction maneuver

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