

Research Advancements in Artificial Intelligence for Space Situational Awareness

Pengrong Hou¹, Zhelong Wang^{1*}, Yu Jiang², Jun Zhu², Qinghao Chu¹, Jiaxi Li¹

¹ School of Control Science and Engineering, Dalian University of Technology, Dalian, China

² State Key Laboratory of Astronautic Dynamics, Xi'an Satellite Control Center, Xi'an, China

{hpr_mail, jiangyu_xian_china}@163.com, wangzl@dlut.edu.cn, zhujun9306@126.com, {Chu1995, lijiaxi}@mail.dlut.edu.cn

*Corresponding Author: Zhelong Wang Email: wangzl@dlut.edu.cn

Abstract—The increasing of satellite launch missions, collisions and disintegration events of space objects, and the vast number of near-Earth asteroids pose significant challenges to space traffic management. Space situational awareness aims to detect, track, classify, and characterize space objects, as well as assess space events, playing a crucial role in space traffic management. The application of artificial intelligence in space situational awareness has unique advantages, especially in enhancing comprehensive abilities such as knowledge, analysis, and decision-making. Its outstanding abilities in transfer learning and lifelong learning can rapidly address complex and dynamic space detection problems. This paper reviews and analyzes the research progress of AI in space situational awareness in the past five years, focusing on data collection, situational awareness, and decision-making. While discussing the advantages and limitations of technical applications, it addresses the feasibility of applying emerging technologies such as distributed machine learning, knowledge graphs, and multi-agent game theory to future space situational awareness research, considering the characteristics of space data and new requirements. This paper points out the effectiveness and necessity of artificial intelligence in space situational awareness, which can provide reference for strengthening space environmental understanding and promoting relevant research in space traffic management.

Index Terms—Space situational awareness, artificial intelligence, decision-making

I. INTRODUCTION

With the continuous increase of human space activities, the number of space objects has been rapidly growing, including artificial satellites, in-orbit spacecraft, space debris, asteroids, etc. According to authoritative statistics from the U.S. Space Surveillance Network (SSN) (released on <http://celestrak.com/>), as of the end of July 2023, there were over 57,000 cataloged space objects, of which 27,000 are still in orbit. Additionally, billions of small space debris that cannot be cataloged due to the lack of effective observations. The further congestion of the space environment has led to a dramatic increase in collision risks, posing a serious threat to space asset security and space traffic management (STM).

Space debris is widely distributed, moves at high speeds, and possesses significant collision energy. Only space debris with a size of 10 cm or larger can be tracked. However,

collisions with 10 cm debris are sufficient to completely disable satellites, and if further cascading collisions occur, there is a possibility of the long-term concern of the Kessler Syndrome. Additionally, collisions with 5 cm space debris are comparable to automobile impacts and can cause severe damage to satellite internal components. The space community has proposed three response measures: mitigation, remediation, and space situational awareness (SSA), but the execution of these measures still needs improvement. Organizations like SpaceX and OneWeb have proposed large-scale or mega-constellation plans, aiming to deploy a large number of satellites in low Earth orbit for network communication, which will further exacerbate the congestion of space environment [1]. Additionally, the threat of small asteroids cannot be underestimated. With diameters of over 10 meters, they move at ultra-high speeds and pose a serious threat to in-orbit spacecraft and the Earth [2]. To ensure the normal operation of spacecraft, the smooth completion of space missions, and to mitigate the impacts caused by falling space objects, it is essential to further strengthen the ability of SSA. This involves utilizing and understanding the past, current, and future state of the space environment, with the support of extensive space surveillance data.

SSA refers to the comprehensive, precise and real-time detection, tracking and analysis of space objects, in order to ascertain the behavior, intent and characteristics of non-cooperative targets that could potentially threaten in-orbit spacecraft. First, it is necessary to utilize and integrate various detection means including ground-based radar and optics as well as space-based infrared and optics to effectively fuse data from different sources to form a consistent depiction of the space situation. Afterwards, track the targets of interest and preliminarily determine their orbital, attitude, area-to-mass ratio and other attributes as well as potential intent. Finally, further coordinate multiple detection units to achieve persistent tracking, combine the complex and dynamic space environment and real-time situation of both parties, predict the behavior of targets of interest, and plan the flight trajectory of friendly spacecraft. However, due to the surge in space objects, existing collision avoidance procedures and game strategies will struggle to cope with the high-frequency space collision events caused by the new environment. Against this

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background, given artificial intelligence's (AI's) advantages in big data processing, pattern recognition, decision support and other aspects, it has been regarded as the mainstream method for next-generation SSA [3]–[5].

In conclusion, reviewing and discussing the progress of AI applications in SSA is of great value to STM. This paper aims to explore the key aspects of AI in SSA, how it supports ground operators in making decisions, and to contemplate future research directions such as data fusion, collaborative perception, multi-agent systems, etc. It represents a forward-looking study on the sustainable development of the future space environment. In Figure 1, the components under review are arranged in a logical sequence.

The rest of this paper is structured as follows: Section II reviews the reliable data sources developed by different project groups from the data perspective. Section III summarizes AI's analysis and interpretation of data from the perception perspective, focusing on tasks of space object detection, tracking, classification and characterization. Section IV reviews from the decision-making perspective the process of AI translating perceived information into actions, including collision prediction, resource scheduling, etc. Section V outlooks the research prospects and discusses potential challenges.

II. AI FOR DATA COLLECTION

The first part of AI-driven SSA is accurately acquiring space object data and necessary data processing. In this process, it is difficult to obtain massive multi-source heterogeneous actual detected data, and simulated data generated by simulators are used for training AI models. Therefore, the data acquisition methods and key processing technologies in data collection are reviewed and discussed.

A. Data Acquisition

The performance of AI methods highly relies on the availability and quality of training data. So far, the major source of SSA has been the U.S. SSN, whereby the US military selectively publishes two-line element (TLE) data of space objects through Space-Track.org [6], [7]. Nevertheless, the accuracy of TLE reports is limited and varies depending on the object's location and orbit. This could be due to data sensitivity and privacy considerations as space situational data contains important national security information, and space agencies and militaries of all countries strictly control the acquisition and use of real data. Meanwhile, the wide range of space objects and geopolitical influences pose tremendous challenges for all-weather persistent monitoring. In the space domain, it remains very difficult and expensive to obtain complete, labeled, high-quality real data from space detection, especially optical image data. The lack of sufficient annotated space data limits AI research work in the field of SSA.

It is worth noting that researchers have attempted to generate space target datasets using simulators to support dynamic simulation tasks such as target tracking and identification. The designed simulators need to fully consider the optical characteristics of space targets and sensor imaging properties.

They generate realistically featured space target data by autonomously controlling scene settings and target quantities, including processes such as target modeling, environment modeling, sensor simulation, data synthesis, calibration, and validation. Depending on different research focuses (such as sensor types [8], whether jitter occurs [9], image SNR [10], [11], static or dynamic tracking [12], illumination angle), custom simulations and generation of optical images, light curves, and trajectory data for space targets are carried out. To our knowledge, publicly available datasets for the 6D spacecraft pose estimation task include the spacecraft pose estimation dataset (SPEED) [13] and the unreal rendered spacecraft on-orbit (URSO) dataset [14]. For space object detection and identification tasks, the spacecraft recognition leveraging knowledge of space environment (SPARK) dataset is available [15]. For 3D trajectory estimation, the SPARK-T dataset can be used, where "T" stands for trajectories [16]. These datasets serve as valuable resources for scientific research and development in the respective areas of space technology and pose estimation, enabling researchers to evaluate and advance their algorithms and methods. A comparison of this paper with examples of public space debris databases is also presented in TABLE I.

In addition, to improve the usability of images for downstream tasks and the monitoring efficiency of SSA, diffusion models have been applied for low-light image enhancement (LLIE) of spinning objects in space [17]. This method can effectively restore image details and improve contrast, outperforming traditional methods in both subjective visual effect and quantitative metrics. This indicates that data-driven image enhancement methods have promising prospects for space object image processing, but the generalizability and adaptability of this method to space scenes need further verification.

In contrast, some researchers have paid attention to the issue of data deception for space objects. Most satellite operators cannot independently obtain SSA data and have to rely on a few centralized repositories operated by major space powers. Given the intensifying competition among nations over space orbits, the threat of abusing such shared information to attack is also increasing. Reference [18] first proposed defense techniques against SSA deception, and then developed a machine learning-based anomaly detection tool that enables defenders to still detect 90%-98% of deception attempts without space detection sensors.

B. Data Processing

Data processing refers to the process of processing, analyzing and extracting useful information from space big data. It is a prerequisite for SSA and plays a critical role in promoting space exploration and application. Space objects possess attributes such as extensive operational trajectories and rapid flight velocities. Depending exclusively on an individual sensor fails to deliver effective coverage and precise tracking across their whole trajectories [19]. Consequently, collaborative measurement through an integrated space-ground surveillance network is imperative, yielding observed data with

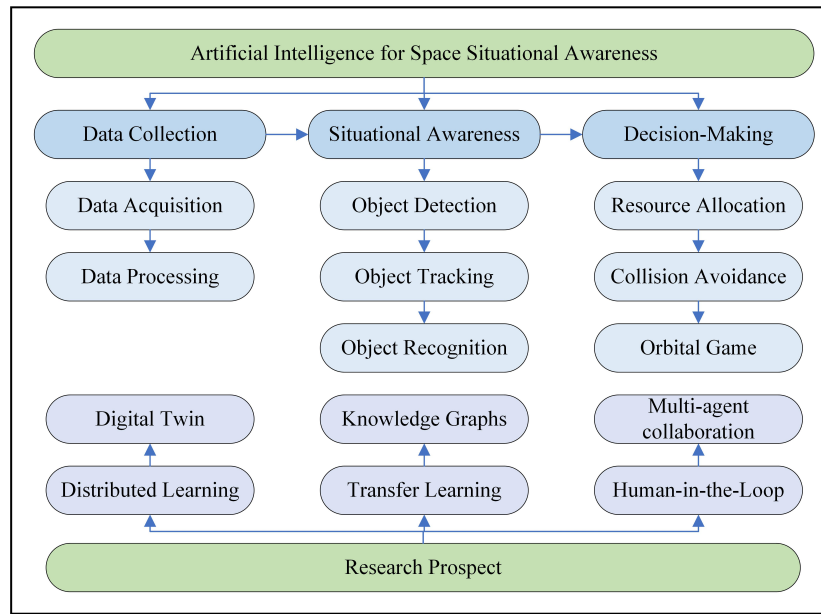


Fig. 1. Reviewed components of AI for space situational awareness.

TABLE I
EXAMPLES OF PUBLIC SPACE DEBRIS DATABASES

Database	Owner	Uses
TLE	US military	Tracking and Prediction; Space Situational Awareness; Orbit Analysis; Satellite Catalogs
SPEED	Kisantal Mate, Sharma Sumant and Park Tae Ha	6D pose (spacecraft)
URSO	Proença, Pedro F and Gao, Yang	6D pose (spacecraft)
SPARK	Musallam Mohamed Adel, Ismaeil Kassem Al and Oyedotun Oyebade	3D model and 6D pose (spacecraft and space debris)
SPARK-T	Musallam Mohamed Adel, Ismaeil Kassem Al and Oyedotun Oyebade	3D trajectory estimation

qualities like multi-station, multi-temporal, massive volume, multi-modality, and varied detection accuracy. Effective fusion and processing of the data information obtained by each sensor can maximize the role and capability of SSA.

As a branch of AI, multi-source information fusion aims to integrate partial and incomplete information from different sensors, data sources, or origins. It eliminates redundancy and contradictions among sensor information, forming more comprehensive, accurate, and reliable fusion information, thereby enhancing the awareness and understanding of space situations. However, multi-source information fusion methodologies customarily necessitate accounting for factors like information origin uncertainty and weight distribution, to guarantee ensuing consolidation output is coherent and reliable. In the field of SSA, multi-source information fusion holds significant advantages in enhancing information, expanding spatio-temporal coverage, and supporting intelligent decision-making.

Multi-source information fusion can be divided into three

levels: data fusion, feature fusion and decision fusion. Data fusion involves registration, calibration and normalization of data from different sensors such as radar, optics and infrared, to achieve information compensation and data augmentation between different data sources. Kalman filter-based trajectory prediction is a typical example of data fusion [20].

Feature fusion conducts analysis after extracting features from data sources and supports subsequent decision making. In SSA, features can be manually extracted features such as orbital parameters, position coordinates, area-to-mass ratio, projected area, or automatically extracted features by artificial neural networks (ANN) [21]. By feature fusion, fusing the feature information extracted from different data sources can enhance the capability of space object detection and tracking, thereby improving the accuracy and robustness of SSA. The research on detection of space debris founded on multi-modal fusion used neural networks to automatically extract deep features from RGB and depth images before fusing them, finally deploying a classification head to actualize target

detection. This is an end-to-end feature fusion method [22].

For decision fusion, when different sensors or algorithms give inconsistent judgments about the same space object, methods like the Bayesian inference [23], the DS evidence theory [24], and ANN have been used to obtain comprehensive and reliable conclusions, thereby enhancing the intelligence and decision support capabilities of SSA.

AI plays a crucial role in data collection for SSA, involving aspects such as data augmentation, data generation, fraud detection, and multi-source information fusion. Among these, multi-source information fusion can enhance the understanding of the SSA by combining information from different sensors. This is highly beneficial for identifying and tracking space objects, as well as predicting space events.

III. AI FOR SITUATIONAL AWARENESS

In SSA, the second part focuses on how to collect, integrate, analyze and understand various data and information from the space environment, in order to gain comprehensive cognition and understanding of space situation. Its core task is to accurately detect and track space objects, determine important characteristics of space objects that may pose threats to on-orbit spacecraft such as size, shape and orbital parameters, and then evaluate target characteristic data to support STM.

The application areas of AI methods in the situational awareness of the space environment include monitoring, tracking, and identification of space objects. This subsection will focus on the latest advancements in these tasks, particularly the application of deep learning. The feasibility of using deep learning for SSA was demonstrated in an industrial study in 2020, where they proposed employing deep learning for achieving space scene perception [25].

A. Object Detection

Object detection aims to identify and locate target objects in space, including in-orbit satellites, manned spacecraft, rocket stages, space debris, asteroids, etc. Object detection is a critical part of SSA. By analyzing and processing space data, it helps determine the target's location, size, shape and other relevant attributes, thereby supporting real-time monitoring and tracking of space objects. However, space object detection still faces many challenges, influenced by factors like complex background and occlusion, scale variation, complex illumination and weather conditions, diversity of target types, etc. Consequently, adaptive, robust space object detection algorithms necessitate development and refinement, encompassing data augmentation, deep learning, etc, to elevate space object detection accuracy, efficiency, and reliability.

Numerous techniques have been engineered for space object detection. For example, when conducting optical observation of artificial objects (satellites, space debris) in geosynchronous orbit, the targets can easily be overwhelmed by background noise due to long distance, presenting weak optical signals. Reference [26] proposed a multi-target detection technique based on topological scanning, utilizing geometric duality to extract approximate linear trajectories of targets from massive

clutter and noise. Topological scanning serves as a traditional method for object detection, presenting clear benefits in specific scenarios and problems. It is particularly suitable for complex morphologies and limited samples in tasks related to detecting multiple classes of objects. Nevertheless, considering constraints like processing efficiency, target restrictions, and noise occlusion, combining with AI methods like deep learning may achieve better performance for more complex object detection tasks [27].

Convolutional neural networks (CNNs) are the most common in object detection tasks, owing to their effective ability to learn image features. They can automatically ascertain local and global image traits, boasting translation invariance enabling localization of target positions and bounding boxes in imagery. However, the complexity of using CNNs for space object detection lies in: 1. Real data has varying SNR; 2. Lack of standard simulated datasets. Among them, networks like CSAU-Net [28] and EfficientDet-EfficientNet [22] used blurring and noise injection for data augmentation to improve object detection accuracy and reduce missed and false detections. Conversely, to address prospective noisy labels from false positives in small debris detection scenarios, a new noisy label learning paradigm called the co-correcting algorithm was proposed, with the goal of maintaining high space debris detection rates under high noisy label rates [29]. Moreover, a space target detection algorithm based on saliency detection was effective in dynamically capturing small debris in videos with low signal-to-noise ratios, demonstrating robustness in detecting low signal-to-noise ratio moving space debris [30].

In summary, deep learning methods, especially CNNs, have shown great potential in object detection in complex space environments by effectively learning features. Such applications are expected to address challenges related to SSA in orbital spacecraft missions.

B. Object Tracking

Object tracking is a critical component in the perception stage of SSA, aiming to accurately track and continuously monitor the motion states of space objects, providing key data support for subsequent analysis and decision-making. Meanwhile, object tracking techniques need to overcome the complexity of space environments and uncertainties in target motions, such as weak signals under long-distance detection, potential occlusions and crossover motions between targets. Therefore, reviewing key technologies pertinent to object tracking is of great importance for further research on SSA.

1) *Orbit Determination*: Orbit determination is the first step, aiming to determine the orbital motion and position of the target. Orbit determination obtains the initial orbital parameters of the target, providing basic data for subsequent orbit prediction and orbit tracking. The problem of orbit determination can be seen as a regression task, crucially utilizing multiple short-arc observation data points, mapping to target positions and velocities across discrete time points. The weighting distribution-regression OD (WDR-OD) method [31] was used for orbit determination of space objects in

geosynchronous orbit (GEO). This method outperformed the improved Laplace method proposed in Reference [32] under white Gaussian noise and colored noise. Moreover, support vector machines were used to reduce position errors of space objects after orbit determination and propagation [33].

2) *Orbit Prediction*: Orbit prediction is the next step after orbit determination, aiming to predict the position, velocity and trajectory of the target over a prospective timeframe based on the obtained initial orbital parameters and orbital mechanics or physics. Orbit prediction is crucial for target tracking and orbit planning. However, existing orbit prediction algorithms face intractability due to sparse, low-precision observations, unknown target geometry, and simplified force models. Leveraging machine learning techniques to ascertain latent orbit prediction error patterns from historical data [34]–[37] or directly deploying them for orbit forecasting can dramatically enhance prediction precision [38]–[40]. Further, by integrating machine learning methods with traditional orbit prediction methods to establish a hybrid analytic-machine learning framework, the accuracy of orbit prediction can be greatly improved [20], [41], [42].

3) *Trajectory Tracking*: Trajectory tracking utilizes the orbital information obtained from orbit determination and prediction, combined with sensor data, to monitor and track the target's position and motion in real time. For space object tracking scenarios restricted to angular data, multistage version of the expectation-maximization (EM) algorithm was utilized for probabilistic data association and orbit parameter estimation [43]. In the collaborative tracking of uncooperative targets by multiple satellites, researchers have validated the accuracy of applying particle swarm optimization [44], consensus-based unscented information filter [45], and distributed spherical simplex information-weighted consensus filter for space tracking [46].

4) *Maneuver Detection*: Maneuver detection is performed by analyzing the motion and trajectory of space objects to determine the type and characteristics of their maneuvers, enabling dynamic monitoring of target motion states for better understanding of target intent and behavior patterns. For orbital maneuver detection of space object, hypothesis testing techniques have been used to analyze target orbital data and determine whether the target is in a maneuvering state [47], [48], effectively mitigating false positives and elevating detection accuracy and reliability. Subsequently, addressing the limitation of traditional Kalman filter algorithms unable to work in the maneuver detection task for non-cooperative targets, improved methods such as extended Kalman filters [49], augmented unbiased minimum-variance input and state estimation (AUMVISE) method [50], etc., were proposed for unknown maneuver detection. In addition, two adaptive consensus-based unscented information filters were proposed for tracking targets with maneuvers and colored measurement noise [51]. These advancements contribute to enhancing the maneuver detection capabilities in the field of SSA.

C. Object Recognition

Given the increasingly congested space environment, practical and feasible methods for space target identification have become crucial to ensure the safety and efficacy of space activities. Urgent research is needed on issues like how to rapidly and accurately identify and track space objects under limited observation conditions. These efforts will provide data support for collision warnings and space mission planning. Therefore, conducting a review and retrospective analysis of research related to space objects holds guiding significance for maintaining space safety and sustainability.

1) *Object Identification*: Object identification aims to obtain object categories and determine key characteristics such as shape, mass, and material by analyzing multi-source sensing data such as radar and optics. In this process, the first step is to preprocess the acquired data and extract features that can represent the salient characteristics of the object. Then, AI methods are used for object classification and identification to determine the type and attributes of the object. Meanwhile, object identification techniques also include estimation of key object features such as mass, material, etc., which play an important role in subsequent object tracking and dynamic behavior analysis. Due to the uniqueness of imaging perspectives, directly applying AI methods to space object identification faces severe challenges of diverse object orientations. Learning and extracting invariant features is a huge challenge for space object identification. Based on basic frameworks such as CNN and Transformer, Researchers have explored various deep neural networks, such as RSONet [52], D2N4 [53], MLP-Mixer [54], and VIT [55] for target classification, and made great breakthroughs [56]. Additionally, they have investigated how to use light curves to differentiate unknown targets [57], [58] and how to calculate target centroids [59], [60] and aspect ratios [61].

2) *State Estimation*: The state estimation of space targets refers to the process of inferring and estimating various key state parameters, including trajectory estimation, attitude estimation, and operational status. Accurate state estimation is crucial for achieving comprehensive awareness and planning of space targets. Hence, reviewing and analyzing state estimation associated techniques are indispensable components of AI-driven research in SSA, providing valuable support to enhance the safety and effectiveness of space activities.

Trajectory estimation aims to analyze and model historical trajectory of the target to predict its possible future trajectory. Since space trajectories have strong correlations in both time and space dimensions, a single image perspective is insufficient to determine its 3D position. However, by continuously capturing dynamic images of a space target using a single camera and employing a two-stage computation, it is possible to obtain a time-consistent 3D position trajectory [62]. Additionally, Reference [63] actualizes a recurrent convolutional neural network (R-CNN) for space object position and velocity estimation under low resolution imaging circumstances.

Attitude estimation aims to infer the orientation and attitude parameters of space objects, such as attitude angles

and angular velocities. Numerous attitude estimation methods have been developed for space objects. The current precise measurement of on-orbit attitude for space objects relies on high-quality, continuous, high-resolution imaging perception through radar and optics. The estimation of target state parameters is based on feature matching of observed data and historical accumulated observation databases. However, the lack of support from observational physical models results in limited estimation accuracy and difficulty in extending to practical application scenarios involving complex moving targets and non-cooperative objects. For instance, utilizing single-station Inverse Synthetic Aperture Radar (ISAR) to observe targets and subsequently employing Hidden Markov Models to describe the changes in target projection [64], [65]. Additionally, there are applications involving the fusion of optical and ISAR data to estimate the instantaneous attitude of space targets [66], [67], as well as the use of multi-station ISAR collaboration for dynamic attitude estimation of spinning spacecraft [68]. In comparison, deep learning has seen limited but promising applications in space object attitude estimation, and has succeeded under different observation conditions like light curves [69], monocular vision [70], video frames [71], etc. It enables precise capture and analysis of space object attitude changes, providing more reliable support and guidance for collision prediction and orbital maneuvering.

In addition, Reference [72] proposed a method for detecting satellite operating status based on photometric reflection characteristics, which can serve as a basis for rapid detection of GEO satellite operating status.

In summary, state estimation of space objects is important for SSA. Further research on related technologies such as trajectory estimation, attitude estimation, operating status assessment, etc. can promote the development of SSA and provide more reliable and accurate data support for the safe and effective management of space activities.

IV. AI FOR DECISION-MAKING

The third part of AI-driven SSA involves the process of transforming spatial environmental information into actions using AI. Decision-making may entail resource allocation, collision evasion, orbital maneuvering, etc. This section will review and discuss key AI technologies in resource scheduling, collision avoidance and orbital maneuvering.

A. Resource Allocation

For the requirements of building a collaborative space object monitoring system, flexible and reasonable task allocation of sensors in the distributed network is needed. In the process of sensor allocation, multiple factors must be considered comprehensively, including timely information acquisition, rapid decision-making in complex environments, and maintaining certain coverage over long periods. Sensor task allocation must have intelligence and adaptability to cope with changing monitoring needs and environmental conditions. With advanced AI technologies, sensor allocation schemes can be

further optimized for better balancing observation accuracy and energy consumption.

The explosive growth of space debris and implementation of mega-constellation missions have made space monitoring tasks more complicated than before, requiring new resource scheduling methods to meet new demands. In early studies, the scheduling problem was viewed as how to effectively allocate sensor observation time for space object acquisition and measurement. The NICO scheduler coordinates user requests under meteorological and astronomical constraints, with the core being using genetic algorithms to solve resource scheduling problems [73]. Moreover, scheduling methods based on tabu genetic algorithms [74], hypothesis and covariance [75] have been developed to improve solving speed and inference accuracy. Additionally, game theory has great potential in solving resource scheduling problems. Reference [76] proposed a self-organized space object tracking method that transforms the resource scheduling problem into a potential game where participants need to follow synchronous best response dynamics to update actions, achieving significantly improved tracking accuracy. Similarly, by considering causal relationships, deep reinforcement learning based resource scheduling solutions have been proposed, improving tracking accuracy while enabling the model to potentially explain the learned policy [77].

B. Collision Avoidance

With the rapid growth of space activities and the increasing space debris, asteroids and other objects, protecting space assets from collisions has become an urgent issue. The key of collision avoidance technology lies in achieving safe navigation of in-orbit spacecraft through accurate collision prediction and flexible maneuver strategies. The core is collision probability calculation and maneuver strategies.

1) *Collision Probability*: Regarding collision prediction, the influence of atmospheric drag uncertainty on initial covariance propagation is frequently discounted, which severely limits the prediction accuracy, especially for low Earth orbit (LEO) applications. The CARA algorithm accounts for such uncertainties, proposing a collision probability calculation method based on Monte Carlo covariance evolution [78]. Despite high accuracy, it is extremely sluggish, only applicable for limited controlled, critical space object collision evolution computation, inept at addressing large-scale orbital collision alerts induced by increasingly elaborate space environments [79]. In this case, an AI-driven collision prediction system has been proposed. Based solely on initial Keplerian elements, a group of ANNs predict satellite state vectors over a period [80]. This method does not rely on any dynamic models or integration during propagation, thus faster execution. In practice, measured data is required to dynamically correct the orbit prediction covariance for rapid, high-precision orbit error propagation to provide timely and reliable collision warnings.

2) *Maneuvering Avoidance*: Maneuver avoidance strategies aim to avoid potential collision risks through flexible maneuvering [81]. For relative distance calculation and maneuver strategy design, the sliding mode control strategy based on

artificial potential function can ensure the convergence of relative position and attitude errors while avoiding collisions [82]. Reference [83] proposed an exploration-adaptive deep deterministic policy gradient (DDPG) algorithm that reduced energy consumption by 16.44% in the close proximity phase compared to the above artificial potential function method. Moreover, integrating meta-learning can promptly train control policies applicable to other perturbed scenarios in a short period of time.

C. Orbital Game

Orbital maneuvering refers to the process of two or more space objects dynamically changing their relative poses through active control under their respective allowable control capabilities and available information support. Pursuit-evasion is a typical example of orbital maneuvering that aims to support the overall space maneuvering strategy to gain space dominance.

Many AI-driven orbital maneuvering techniques have been developed. Reference [84] transformed the original pursuit-evasion problem into a 4-dimensional one-sided optimal control problem (OCP) and established the mapping between OCP and its solution using deep neural networks, thus solving the pursuit-evasion game for free-time elliptical orbits. Reference [85] modeled the pursuit-evasion problem as a differential game and given a closed-form boundary solution. Near-optimal interception strategies in orbital pursuit-evasion were obtained through deep reinforcement learning. Reference [86] transformed the pursuit-evasion problem into a bilateral optimization problem. To determine the optimal impulsive actions for both players, the PRD-MADDPG algorithm based on multi-agent reinforcement learning framework was designed. Results showed this method can effectively find applicable policies even under more complex constraints.

In summary, orbital maneuvering techniques can cope with more complex space environments and have good generalizability and adaptability with the help of deep reinforcement learning. However, the above algorithms assume that the game is fully observable, whereas in practical applications, there may be unknown hostile targets that need to be quickly discovered, tracked in real-time, or timely evaded, requiring stronger situational awareness capabilities.

V. RESEARCH PROSPECTS

In the above research, the key technologies of AI for space situational awareness are reviewed and discussed along the three levels of data, perception, and decision-making. On this basis, this section will look forward to how AI can further serve space situational awareness.

A. Data Collection

Accurate space observation data is vital. These sources encompass ground-based radar, optics, laser ranging, and space-based infrared, optics, and passive sensing, which are crucial for target detection, tracking, identification, and maneuver control. The above data often involves national security and

is difficult to obtain directly. Even public data sources have limited coverage and accuracy. AI new technologies have unique advantages in dealing with limited data and data security.

- Use of digital twin technology: Simulators can be used to mimic real scenarios to generate virtual space object data. These simulators can be built based on digital twin technology to provide high-fidelity simulated space object data, but the match between the data and real scenarios needs attention.
- Use of distributed machine learning: With the precondition of data security, establish international collaborative mechanisms to jointly conduct space debris monitoring and tracking. The introduction of advanced technologies like federated learning can promote global cooperation, information sharing and technological innovation without compromising privacy, thus better addressing the growing space debris problem.

B. Situational Awareness

The current space situational awareness capability is still relatively limited, mainly manifested in insufficient monitoring capabilities and insufficient use of AI technology. The existing monitoring network has poor monitoring capabilities for small targets and high-orbit targets, and the monitoring and identification of electromagnetic and optical characteristics of space targets is not fine enough, and the capabilities of AI in knowledge representation and transfer learning have not been fully utilized. Therefore, it is worthwhile to further improve the direction of SSA.

Currently, SSA's capabilities are still limited, mainly manifested in insufficient monitoring capabilities and underutilization of AI technologies. Existing monitoring networks have poor capabilities in monitoring small objects and high orbital targets. Monitoring and identification of electromagnetic and optical characteristics of space objects is not refined enough. AI capabilities in knowledge representation, transfer learning, etc. have not been fully utilized. Therefore, directions worth further research include

- Application of knowledge graphs: Knowledge graphs can be used for knowledge representation and reasoning in SSA, to better organize representations of connections between space objects and behavior events, and conduct knowledge-based advanced reasoning such as target detection, tracking, and identification.
- Application of transfer learning: Transfer learning can transfer knowledge learned from the source domain to the target domain. SSA involves diverse environments and scenarios, and the corresponding detection data distributions may differ. Domain adaptive techniques can improve the consistency of cross-regional space object identification, and weak supervised transfer learning can improve detection capabilities for newly discovered space objects.

C. Decision-Making

Existing ground-based radar, optics and other detection devices have limited coverage of space, and are subject to geographical constraints. The received signal strength is inversely proportional to the distance to the observed target. To compensate for the inadequacy of ground monitoring networks, space-based optical sensors are used for high orbit target detection. To improve tracking performance, multiple satellites are needed to perform the task. How to maximize consumption reduction while obtaining better awareness is a direction that needs further thinking.

- Multi-agent collaboration: Multi-agent cooperative algorithms can effectively coordinate ground radar, optical sensors and satellite infrared, optical devices to achieve more efficient distributed space monitoring.
- Human-in-the-Loop: Establishing a human-machine hybrid decision system that leverages AI for monitoring and prediction while also incorporating expert experiential strategies to achieve collaborative response in SSA. Furthermore, through interactive learning, AI continuously acquires expert prior knowledge to enhance the overall effectiveness of space monitoring and threat assessment.

VI. CONCLUSION

In recent years, AI with key technologies such as deep learning and reinforcement learning as the core and supported by big data and cloud computing has shown a blowout explosion, showing excellent performance in SSA. Therefore, the application of new AI technologies to SSA has good prospects for development. It is foreseeable that digital twins, distributed machine learning, knowledge graphs, transfer learning, multi-agent collaboration, and human-machine collaboration are key research directions for future SSA. Here, the key conclusions and insights of the paper are summarized as follows.

- To further enhance space situational awareness capabilities, in the context of a unified space monitoring network combining space-based and ground-based assets, dynamic optimization and management of multiple sensors can be employed to achieve optimal system performance. Through data fusion, integration of data from different sensors can provide a more comprehensive and detailed situational awareness information.
- At present, the related research on AI-driven space situational awareness mainly focuses on the detection, tracking and identification of space targets. Due to occlusion, aliasing, damage, interference, etc., the macroscopic and microscopic characteristics of the target change with time, and there are obvious differences between the actual image and the simulated image. The target detection and recognition task faces the dual difficulties of feature uncertainty and sample scarcity. Therefore, it is necessary to propose an automatic data enhancement method for spatial object detection and recognition to improve the adaptability of the model to the characteristic changes of spatial objects according to the characteristic changes of typical objects.

- For the orbital game problem under the condition of incomplete information in a complex space environment, the knowledge and computing power that a single agent can obtain are limited, and it is difficult to deal with various uncertain factors. Consider combining deep reinforcement learning technology to carry out research on modeling and solving multi-agent large-scale game problems, make full use of the interactive information of multi-agents, and adaptively adjust environmental parameters to improve the global strategy learning ability.

In conclusion, progress has been made in AI-powered SSA, enabling the technological development of a new generation of STM. This work reviews and discusses these key technologies, hoping to guide future research in this field.

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