ORBIT: Open-Source Research for Better Identification and Tracking of Space Objects

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Abstract

With nearly 40,000 resident space objects (RSOs) currently being tracked by space surveillance networks in Earth's orbital space—a number expected to rise significantly—managing these objects has become an increasingly urgent challenge. To prevent collisions and ensure the long-term sustainability of space operations, robust techniques for detecting and tracking RSOs are essential. This study introduces ORBIT (Open-source Research for Better Identification and Tracking of Space Objects), a web-based platform designed to analyze user-uploaded night-sky image sequences using the PFT+ (Proximity Filtering and Tracking) algorithm. The algorithm's performance was evaluated using the stratospheric SSA dataset, achieving an average precision of 98 %, recall of 76 %, and an F1 score of 86%, thus demonstrating high accuracy while reducing the need for manual annotation.

To further refine detections, ORBIT integrates a GUI-based manual annotation tool, enabling users – including amateur astronomers and global researchers – to contribute their data, validate algorithm results, and build improved SSA datasets. By democratizing SSA data contribution, ORBIT mitigates information bias, expands training datasets for AI-based tracking, and fosters global collaboration in space monitoring. Additionally, ORBIT supports continuous development and benchmarking of detection algorithms, facilitating innovation in space debris tracking and collision avoidance. This paper presents ORBIT's system architecture, algorithmic framework, dataset utilization, and performance evaluation, demonstrating its role in enhancing SSA and ensuring sustainable space operations

Keywords: Space Situational Awareness (SSA); Resident Space Objects (RSOs); Space Sustainability; Web-based platform; Space Object annotation; Citizen Science

Acronyms/Abbreviations

AI Artificial Intelligence
COTS Commercial Off-The-Shelf
CSV Comma-Separated Values
ESA European Space Agency
GUI Graphical User Interface
ID Identifier
ORBIT Open-source Research for Better Identification and Tracking of Space Objects
PFT+ Proximity Filtering and Tracking Plus
PNG Portable Network Graphics

RSOs Resident Space Objects
SSA Space Situational Awareness
SSM Star Stare Mode
SSN Space Surveillance Network
SST Space Surveillance and Tracking
WFOV Wide Field Of View

1. Introduction

Space Situational Awareness (SSA) encompasses the detection, tracking, and characterization of objects in Earth's orbital space. It is a critical component of modern space operations, ensuring safety and sustainability in an increasingly congested orbital environment. With the rapid proliferation of satellite launches and mega-constellations, the number of operational spacecraft and inactive debris has risen sharply, exacerbating the risk of on-orbit collisions. As global dependence on satellite services continues to grow, the need for accurate, continuous monitoring of resident space objects (RSOs)—including active satellites and orbital debris—has become imperative.

As of April 4, 2025, Space-Track approximates 11,400 active payloads and 18,800 cataloged debris objects in Earth's orbits [1]. Additionally, the U.S. Space Surveillance Network (SSN) tracks approximately 17,500 further uncatalogued objects, which are monitored to assess their potential correlation with known launches [1]. However, most high-fidelity SSA systems, such as the U.S. SSN and the European Space Agency's Space Surveillance and Tracking (SST) network, are operated by governmental or military agencies. Their datasets are often not publicly accessible, while commercial SSA services typically require costly subscriptions. These limitations pose a significant challenge for researchers, educators, and citizen scientists seeking to participate in SSA activities.

Amateur astronomers and hobbyist observers typically rely on personal telescopes and optical sensors to acquire imagery for SSA purposes. However, detecting RSOs against the star field is non-trivial. Under short exposures, RSOs appear visually indistinguishable from stars. Under long exposures, faint RSO streaks may be difficult to identify due to background noise or blending with celestial features, making manual detection both technically demanding and time-consuming.

Several rule-based and AI-based approaches have been developed to address RSO detection in optical imagery [2,3]. However, many of the AI models rely on synthetic or semi-synthetic datasets, in which object labels are algorithmically generated post-rendering. While these synthetic datasets provide scalable ground truth, they often fail to replicate real-world imaging conditions—such as sensor noise, airglow, or cloud cover—leading to reduced model generalization when applied to actual observational data. Moreover, generating ground truth labels for real images requires domain expertise and substantial manual effort, creating a bottleneck in the development and validation of machine learning-based SSA tools.

Citizen science has shown significant promise in other domains involving large-scale data annotation. NASA-led open science programs such as Active Asteroids, Daily Minor Planet, and ExoAsteroids have successfully engaged the public in tasks such as object labeling and classification, resulting in meaningful scientific contributions [4-6]. Furthermore, annotation frameworks like ActiveAnno and ViTBAT have demonstrated that well-designed interfaces can enable efficient human-in-the-loop annotation while minimizing cognitive load [7,8]. However, to date, there exists no publicly accessible platform tailored specifically for annotating space object imagery in support of SSA.

In response to these challenges, we introduce ORBIT (Open-source Research for Better Identification and Tracking of Space Objects)—a web-based, open-source platform that facilitates the detection, annotation, and refinement of RSOs in optical imagery. ORBIT automates the initial identification and labeling of RSOs using the PFT+ (Proximity Filtering and Tracking Plus) algorithm and enables users to refine and validate results via an interactive graphical interface. By combining computational detection with distributed user engagement, ORBIT aims to significantly expand the volume of high-quality annotated SSA datasets while democratizing participation in space traffic management research.

This paper is organized as follows: Section 2 describes the architecture and components of the ORBIT platform, including the web interface, PFT+ detection algorithm, manual annotation tool, and the dataset used. Section 3 presents experimental results evaluating detection accuracy and implementation. Section 4 discusses the implications of our findings for SSA workflows and future research. Finally, Section 5 concludes with a summary of contributions and future directions.

2. Methodology

ORBIT is a web-based platform that enables users to upload image sequences, perform automated detection of RSOs using a server-side algorithm, and review results through an interactive graphical interface. The system architecture presented in fig. 1, includes a backend server for image processing and data management and a frontend interface accessible via standard web browsers. This architecture ensures broad accessibility; contributors require no specialized hardware or software to participate.

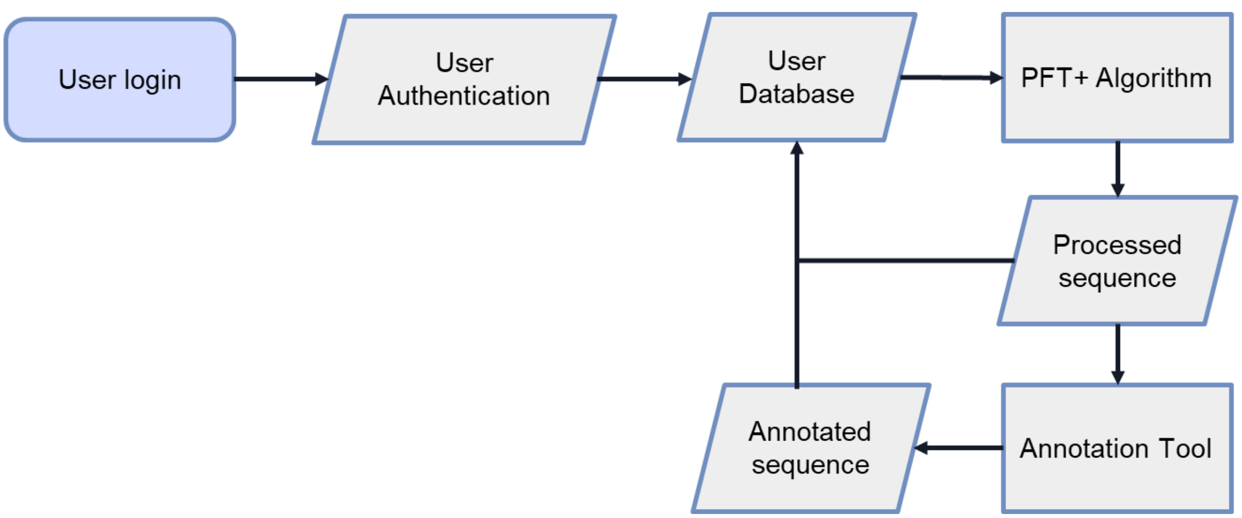

Fig. 1. System architecture and data flow in ORBIT: users upload image sequences, which are processed server-side using PFT+. Results are stored in a user profile and made available for review, download, or further manual annotation.

Uploaded images are stored in a secure database and processed using the PFT+ algorithm. The annotated outputs—overlay images and metadata—are saved to each user's profile. A secure login system supports registration and password recovery. The platform follows best practices in web security and scalability, allowing seamless onboarding of new users and secure, isolated storage of user-contributed data.

2.1 Web Platform.

The ORBIT interface is designed to lower the technical barrier to participation and promote inclusivity in SSA research and data collection. The ORBIT web interface offers the following core functionalities (Shown in fig. 2):

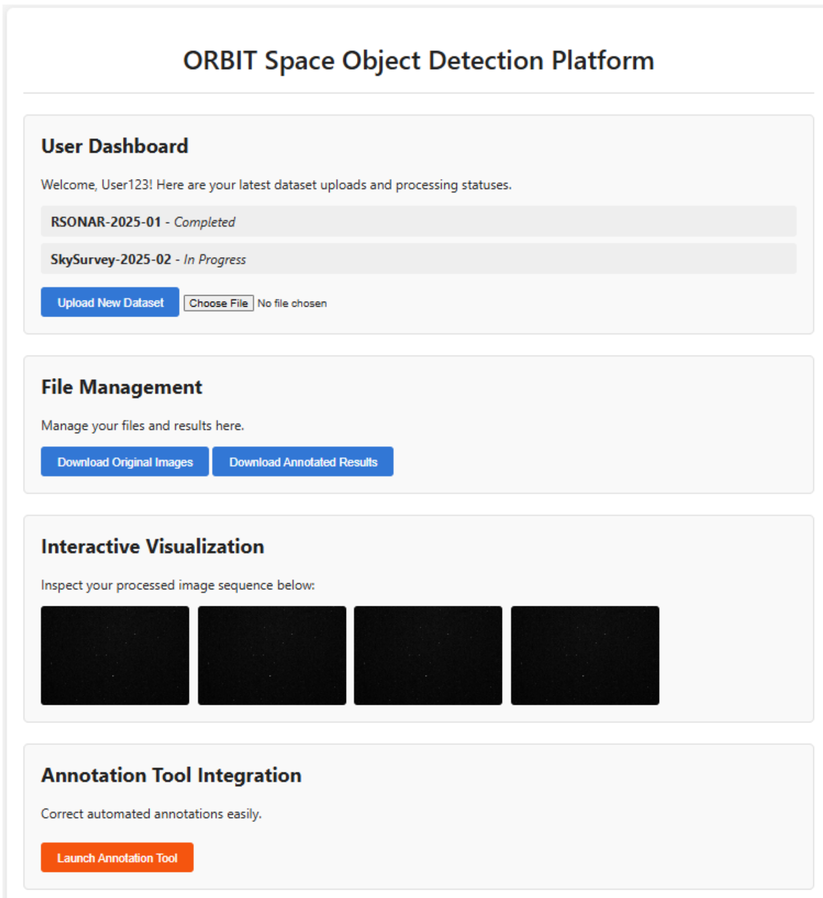

Fig. 2. Screenshot of the ORBIT web interface showing core modules: user dashboard, file management, interactive visualization of detections, and integrated manual annotation tool.

- User Dashboard: After logging in, users can access a dashboard showing their uploaded datasets, processing status, and results. They can initiate new processing jobs by selecting an algorithm (currently PFT+) and uploading a sequence of images (e.g., as a ZIP file).
- File Management: Users can upload bulk image sequences and later download either the original inputs or the processed outputs, which include annotated images and corresponding files.

- Interactive Visualization: Processed sequences are displayed through a frame-by-frame image carousel, allowing users to assess algorithm performance via bounding boxes and labels rendered on detected objects.

- Annotation Tool Integration: If errors are identified in the automated annotations (e.g., false positives or missed detections), users can invoke a built-in manual annotation interface for correction (Section 2.3).

2.2 Proximity Filtering and Tracking Plus (PFT+) Detection Algorithm

At the core of ORBIT's automated processing is the PFT+ algorithm, which identifies RSOs in the stellar background. It extends the baseline Proximity Filtering and Tracking (PFT) method with enhancements in preprocessing, tracking stability, and robustness against noise [2].

The algorithm processes image sequences in the following stages (shown in fig. 3):

- Preprocessing: To prepare for analysis, each image sequence is first normalized to 8-bit grayscale for standard computer vision operations. Each frame undergoes thresholding to produce a binary image where background pixels are black, and any bright pixel (star or RSOs) is white. This step simplifies subsequent detection by reducing noise and variations in brightness.

- Median Frame Differencing: The sequence is divided into segments based on user input. For each segment, a median frame is computed by taking the median of pixel intensities across those frames. In this median image, consistently present objects (stars) appear as bright points, while transient or moving objects and random noise are averaged out and appear dark. Comparing individual frames to the median frame enables the algorithm to isolate static versus moving features as visualized in figure 4. Contour detection on the median frame yields the positions of all stars in that segment, which are stored for further processing.

- Contour Detection and Proximity Filtering: The algorithm detects contours in each frame to locate bright objects. Each detected contour is compared to the list of known star positions from the median frame. Proximity filtering is applied: if a detected object lies within a small radius of detected star, it is classified as a star and excluded as an RSO. This step filters out the majority of detections, leaving only RSO candidates. The proximity threshold is tuned based on expected star drift and image resolution.

- Inter-frame Tracking: Each RSO candidate is assigned a unique identifier. The algorithm performs inter-frame tracking to maintain consistent IDs for the same physical object across the sequence. It matches new RSO candidates to existing ones from previous frames based on proximity and motion direction. If an object follows a consistent trajectory, it is assigned the same ID across frames. If it disappears and reappears after a gap, re-identification is attempted based on predicted trajectory; otherwise, a new ID is assigned.

- Output Generation: For each detected star and RSO, the algorithm records attributes including pixel coordinates, bounding box size, brightness, and object ID. Results are saved as CSV files and annotated PNG images for visualization. These outputs are stored on the server and linked to the user's profile.

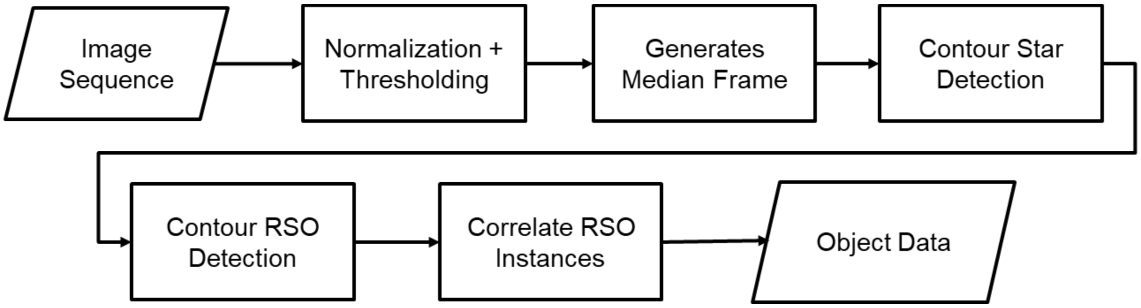

Fig. 3. Functional pipeline of the PFT+ algorithm: from raw image input to star filtering, RSO tracking, and output annotation.

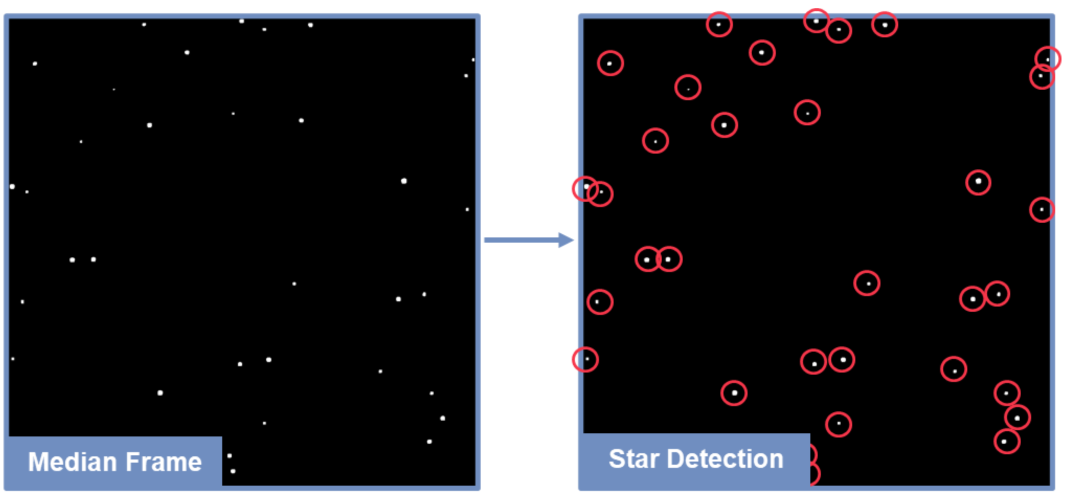

Fig. 4. The median frame (left) is computed from a sequence of images, highlighting static objects such as stars. On the right, detected star positions are identified using contour detection and marked with red circles, enabling static background suppression in subsequent processing.

PFT+ introduces several improvements over the original PFT method. These include size-based filtering to discard spurious detections such as hot pixels or lens flares, and the use of rolling median frame updates to account for slow star field drift. These refinements enhance detection precision without substantially compromising recall. The algorithm was evaluated using standard object detection metrics, including Precision, which measures the proportion of correctly identified RSOs among all detections; Recall, which quantifies the proportion of actual RSOs that were successfully detected; and the F1-Score, which represents the harmonic mean of precision and recall, providing a balanced measure of overall performance.

2.3 Annotation Tool and User Annotation Workflow

While automated detection significantly reduces manual effort, expert oversight remains essential. ORBIT includes an integrated GUI-based manual annotation tool, accessible directly via the web

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interface or available as a downloadable application for offline use (shown in fig. 5). This tool allows users to refine annotations, improving the dataset's accuracy over time and engaging citizen scientists in the process. Once annotations are completed, the corrected data is seamlessly integrated into ORBIT's growing repository of labeled observations.

In the annotation tool, users can:

- Add Bounding Box: Users can draw a box around objects to be labeled. New annotations can be tagged as "RSO," "star," or other relevant labels via dropdown menus or keyboard shortcuts.

- Delete or Modify Annotation: If the algorithm misclassifies an object, users can delete the bounding box or reassign its label. For example, clicking a bounding box and selecting "Mark as Star" or "Delete."

- Save and Submit: Users can save their changes, which are recorded under their profile and can be submitted for verification (optional).

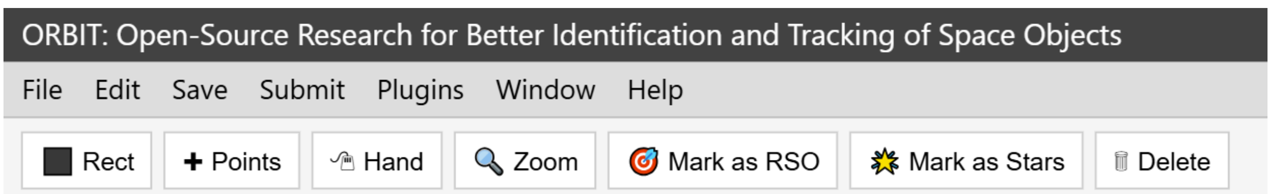


Fig. 5. The ORBIT Desktop interface: the toolbar provides essential functions including rectangular and point annotation choices, panning tool, RSO and star labeling, and deletion.

The interface supports zooming, displays frame metadata, and provides a legend for annotation categories. It is optimized for ease-of-use, enabling efficient review and correction by users of varying expertise levels.

2.4 Dataset Used

The dataset used in ORBIT's development was obtained from the RSONAR (Resident Space Object Near-space Astrometric Research) mission, launched on August 22, 2022, aboard a high-altitude balloon as part of the Stratos-Science program—a collaboration between the Canadian Space Agency (CSA) and CNES [9]. The mission demonstrated a commercial off-the-shelf (COTS), dual-purpose star tracker capable of simultaneous RSO imaging and attitude determination.

During its flight, the platform reached an altitude of 36 km and entered a stabilized pointing phase from 2:56 AM to 5:33 AM local time. Over this 157-minute interval, more than 27,000 images were captured using a 0.1-second exposure, grouped into burst sequences with a 4-second delay between bursts. Imagery was acquired during astronomical dawn, yielding favorable illumination conditions with minimal sensor saturation. Operating in Star Stare Mode (SSM), the tracker captured RSOs as point-like sources due to the high temporal resolution.

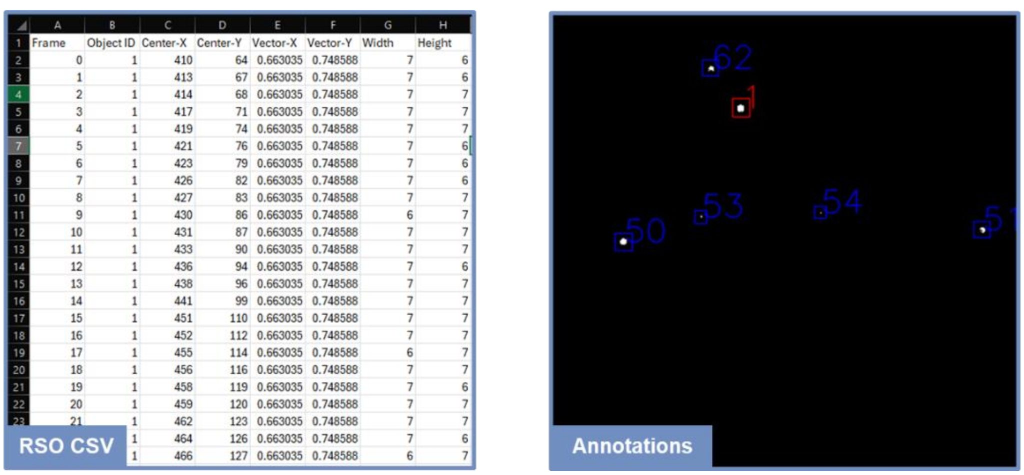
The stratospheric vantage point eliminated the effects of atmospheric turbulence, light pollution, and weather variability. The field of view included star fields from the Pegasus, Equuleus, and Aquarius constellations. This dataset is unique in that, despite being acquired from a pointing platform, the relative positions of background stars remained stable over short time intervals.
The imagery consists of 1024×1024, 16-bit monochromatic frames with a wide field of view (WFOV). Ground truth labels for ~500 unique RSOs were generated manually by SSA researchers, while annotations for 31,759 stars were produced using the Astrometry.net plate solver [10]. The star tracker was capable of detecting stars up to magnitude 8 while the celestial distortion remained within ~ 15 arc-seconds pre-correction.

A subset of this dataset—previously used in [2]—was employed for evaluating ORBIT's detection and annotation performance. This curated collection serves as a valuable benchmark, exhibiting imaging characteristics typical of both ground-based and space-based SSA observations. By leveraging this resource, ORBIT facilitates the development and validation of algorithms for RSO tracking and annotation under real-world conditions.

3. Results

After implementing the ORBIT platform and running the PFT+ algorithm on the test sequences (shown in fig. 6), we obtained quantitative results demonstrating the effectiveness of the approach. Fig. 7. below presents the aggregated results for RSOs and stars across the test dataset.

To evaluate detection performance, we used manually verified labels as ground truth for RSOs and Astrometry.net-generated coordinates for star annotations, which have a reported accuracy exceeding 99.9% in optical imagery [10]. A detection was considered correct if its bounding box overlapped with the labeled object with pixel tolerance. Precision, recall, and F1-score were calculated using these ground-truth comparisons on a frame-by-frame basis.



Frame	Object ID	Center-X	Center-Y	Vector-X	Vector-Y	Width	Height
0	1	410	64	0.663035	0.748588	7	6
1	1	413	67	0.663035	0.748588	7	6
2	1	414	68	0.663035	0.748588	7	7
3	1	417	71	0.663035	0.748588	7	7
4	1	419	74	0.663035	0.748588	7	7
5	1	421	76	0.663035	0.748588	7	6
6	1	423	79	0.663035	0.748588	7	6
7	1	426	82	0.663035	0.748588	7	6
8	1	427	83	0.663035	0.748588	7	7
9	1	430	86	0.663035	0.748588	6	7
10	1	431	87	0.663035	0.748588	7	7
11	1	433	90	0.663035	0.748588	7	7
12	1	436	94	0.663035	0.748588	7	6
13	1	438	96	0.663035	0.748588	7	7
14	1	441	99	0.663035	0.748588	7	7
15	1	451	110	0.663035	0.748588	7	7
16	1	452	112	0.663035	0.748588	7	7
17	1	455	114	0.663035	0.748588	6	7
18	1	456	116	0.663035	0.748588	7	7
19	1	458	119	0.663035	0.748588	7	6
20	1	459	120	0.663035	0.748588	7	7
21	1	462	123	0.663035	0.748588	7	7
	1	464	126	0.663035	0.748588	7	6
	1	466	127	0.663035	0.748588	6	7

Fig. 6. The image on the left displays tabulated detection data, including object ID and position, for Resident Space Objects (RSOs). The image on the right shows an annotated frame from the ORBIT platform. Detected RSOs are outlined in red and labeled with a unique ID number (e.g., "1"), while stars are shown in blue with corresponding ID numbers (e.g., "50–62").

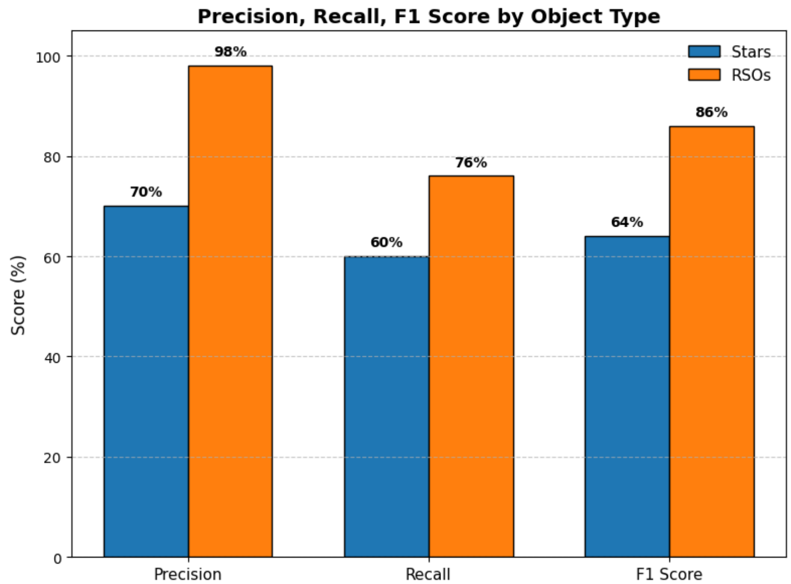


Fig. 7. Evaluation metrics (Precision, Recall, F1 Score) comparison by object type for PFT+ algorithm on the test dataset.

For RSOs, the algorithm achieved a precision of 98%, indicating that nearly all detections classified as RSOs were correct. The recall was 76%, meaning that approximately three-quarters of all actual RSOs present in the imagery were successfully identified. This yields an F1-score of 86%, reflecting a strong trade-off between detection accuracy and completeness.

To further assess the algorithm's filtering capabilities, we evaluated its performance on star detection. The PFT+ algorithm attained a precision of 70%, a recall of 60%, and an F1-score of 64% for stars. These results suggest that while star detection was reasonably accurate, the algorithm's design intentionally suppresses static background objects to minimize false positives in RSO detection. Star annotations were derived using a well-established plate solver with a reported success rate exceeding 99.9% in optical imagery [10]. Therefore, a slightly reduced precision for stars is acceptable and expected.

Overall, the results confirm that PFT+ is highly effective at isolating moving RSOs from celestial backgrounds. It offers high precision in identifying objects of interest while preserving robust recall, even in the absence of manual corrections. This underscores its potential to support the automated generation of reliable training and validation datasets for SSA research.

From a qualitative standpoint, the automated annotations produced by ORBIT were reviewed through the web interface. RSOs were marked with red bounding boxes and ID labels, while stars were bounded in the blue boxes. We observed that bounding boxes consistently tracked the motion of the objects across consecutive frames, confirming that the tracking module effectively preserved object identities. In edge cases where an object briefly disappeared (e.g., due to thresholding variation), the algorithm occasionally generated fragmented tracks with new IDs. These instances were easily resolved using the manual annotation tool, where users could relabel or merge tracks representing the same physical object.

We also evaluated the reduction in manual effort provided by ORBIT. Without automation, annotators would be required to scan every frame manually —and even then, human vision might fail to detect dimmer RSOs. In contrast, ORBIT's algorithm generated only a few candidate detections per sequence—most of which were accurate—thus focusing human attention where it is needed most. In our experiments, expert users were able to review and correct an entire sequence within minutes, whereas full manual annotation would have taken significantly longer. These findings demonstrate that ORBIT can substantially accelerate the development of ground-truth datasets for SSA applications.

4. Discussion

The development of ORBIT addresses several critical needs in the SSA community. The results presented above demonstrate that RSO detection using the PFT+ algorithm can accurately identify objects in dense star-field imagery, laying the groundwork for building large, annotated datasets without prohibitive manual effort. This is particularly significant given the scarcity of open, labeled SSA data.

ORBIT's open-source, web-based approach reduces the reliance on classified or proprietary sources and enables a broader, distributed model of participation. By lowering the technical barrier for contribution, it facilitates global engagement—from amateur astronomers to students and researchers—and supports the creation of scalable datasets that reflect diverse observational conditions. The data collected can be directly leveraged to train and benchmark advanced machine learning models, and in turn, advance automated SSA techniques.

One of ORBIT's strengths lies in its human-in-the-loop workflow. The high precision of the PFT+ algorithm minimizes false positives, while the integrated manual annotation tool allows users to refine uncertain cases—particularly useful in scenarios with image artifacts. This approach combines the scalability of automation with the nuance of expert judgment, as successfully demonstrated in other domains.

4.1 Future work

To improve recall, we aim to integrate more RSO detection algorithms. We also plan to implement a streak detection module for long-exposure imaging [2], and an active learning pipeline in which user annotations iteratively improve the model.

ORBIT will soon be launched as a public beta, supported by outreach to astronomy clubs and academic partners. This deployment will test scalability, gather feedback, and expand the diversity of contributed imagery. Additionally, we are exploring multi-sensor fusion—allowing the same object observed from multiple viewpoints or instruments to be correlated, improving orbit estimation and track continuity.

Technically, scaling ORBIT to support large datasets or real-time operation will require backend optimizations or distributed processing. Cloud infrastructure may be used to parallelize workloads during high-demand periods. In the long term, ORBIT could evolve into a full-featured repository, storing multimodal data such as light curves or spaceborne sensor images [11] to support hybrid analysis and validation. ORBIT provides a flexible and extensible framework for SSA. Beyond its immediate utility for detection and labeling, it promotes public involvement, cross-institutional collaboration, and long-term stewardship of the orbital environment.

6. Conclusion

In conclusion, we introduced ORBIT, an open-source platform for the detection and annotation of RSOs. It integrates a high-precision automated detection algorithm (PFT+) with a manual annotation interface, providing a flexible framework for scalable RSO analysis and public engagement. The system is designed to address the complexities of starfield imagery while remaining accessible through a web-based interface.

Evaluation using a real SSA dataset demonstrated that PFT+ reliably identifies RSOs, achieving an overall precision of 98% and an F1-score of 86%. These results confirm that ORBIT significantly reduces manual labeling effort, helping to overcome a longstanding bottleneck in SSA research. Its built-in human-in-the-loop capabilities further support continual refinement of detection quality, especially for challenging edge cases. ORBIT exemplifies how modern web technologies can support scalable, community-driven SSA. As a foundation for future collaboration, it has the potential to accelerate data generation, foster cross-disciplinary participation, and promote responsible monitoring of the orbital environment.

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