

Algorithmic and Machine Learning Approaches for Space Debris Tracking, Image Enhancement, and Mitigation

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Abstract

The rapid commercialization and exploitation of Low Earth Orbit (LEO) have initiated an unprecedented era of space exploration, shadowed by a critical and exponentially escalating threat: space debris. With millions of hypervelocity fragments currently orbiting the Earth, the risk of catastrophic collisions leading to the Kessler Syndrome has never been more pronounced. Traditional ground-based radar systems and analytical probability models are increasingly insufficient for managing the sheer density of modern orbital environments, particularly concerning debris smaller than ten centimeters. Furthermore, the advent of satellite mega-constellations has multiplied the frequency of required collision avoidance maneuvers, straining existing manual and semi-automated Space Traffic Management (STM) frameworks. This paper establishes the foundational necessity for integrating advanced Artificial Intelligence (AI) into the STM and Active Debris Removal (ADR) pipelines. Specifically, it examines the application of state-of-the-art computer vision architectures—namely YOLO, ResNet, and UNet—for the real-time detection, image enhancement, and semantic segmentation of faint optical streaks produced by sub-pixel space debris. Additionally, it highlights the paradigm shift introduced by Deep Reinforcement Learning (DRL) in autonomous mission planning, where algorithms such as Masked Proximal Policy Optimization (PPO) and Deep Q-Networks (DQN) are utilized to solve complex, dynamic Traveling Salesman Problems (TSP) associated with multi-target ADR missions. By bridging the gap between deep feature extraction for optical tracking and autonomous decision-making for orbital mitigation, this research provides a comprehensive blueprint for next-generation, AI-driven space sustainability.

Keywords

Active Debris Removal (ADR), Collision Avoidance Maneuver (CAM), Deep Reinforcement Learning, Kessler Syndrome, Space Situational Awareness (SSA), UNet, YOLO.

I. INTRODUCTION

A. The Escalating Crisis in Low Earth Orbit and the Kessler Syndrome

Since the launch of Sputnik 1 in 1957, near-Earth space has transitioned from a pristine scientific frontier into a highly congested and hazardous operational environment. Decades of continuous orbital launches, discarded rocket bodies, mission-related anomalies, and catastrophic satellite fragmentations have contributed to a vast and uncontrolled accumulation of artificial material known as space debris¹. While larger derelict objects are routinely tracked by the United States Space Surveillance Network (SSN) and similar global space defense entities, the sheer volume of untracked, millimeter-to-centimeter scale debris poses a severe, dynamic, and poorly characterized threat to current and future orbital infrastructure³. Current models estimate that the orbital environment contains approximately 36,500 objects larger than 10 centimeters, over one million objects ranging between 1 centimeter and 10 centimeters, and an estimated 130 million fragments measuring

between 1 millimeter and 1 centimeter¹. A collision with even a sub-centimeter fragment at typical hypervelocities—often exceeding 7 to 10 kilometers per second—carries kinetic energy sufficient to critically damage or completely destroy an active satellite, as evidenced by a 0.2 millimeter paint fleck severely damaging a Space Shuttle window during the STS-7 mission². This cascading kinetic threat was formally identified in 1978 as the Kessler Syndrome, a theoretical and increasingly empirical scenario wherein the spatial density of objects in Low Earth Orbit (LEO) becomes high enough that random collisions between objects cause a runaway fragmentation cascade². Such a cascade generates exponentially more debris, which in turn causes further collisions, ultimately possessing the potential to render specific orbital regimes completely impassable and unusable for future generations².

The empirical reality of the Kessler Syndrome became starkly evident during landmark orbital fragmentation events over the past two decades. Most notably, the 2007 anti-satellite (ASAT) missile test on the Fengyun-1C weather satellite and the 2009 accidental, hypervelocity collision between the active commercial Iridium-33 satellite and the defunct Russian Cosmos-2251 communications satellite instantaneously added thousands of trackable fragments and millions of untrackable micro-debris particles into LEO². These singular events permanently altered the baseline risk calculus for all subsequent space operations.

B. Debris Growth and the Era of Mega-Constellations

The proliferation of orbital debris is not a linear phenomenon; it is an exponentially compounding crisis exacerbated by the rapid commercialization of space. Over the past three decades, the sheer number of objects launched into space has accelerated, fundamentally altering LEO traffic dynamics¹. Table I illustrates the hypothetical and referenced historical growth trajectory of space debris and active payloads, demonstrating the compounding nature of the problem across distinct eras of space exploration.

Decade / Epoch	Trackable Objects (>10cm)	Estimated Debris (1cm - 10cm)	Estimated Micro-Debris (1mm - 1cm)	Primary Catalysts and Orbital Events
1990 - 1999	~8,000	~150,000	~10 Million	Accumulation from early space exploration, discarded rocket stages, and early payload fragmentation ³ .
2000 - 2009	~14,000	~300,000	~40 Million	2007 Fengyun-1C ASAT Test, 2009 Iridium-33/Cosmos-2251 collision generating massive debris clouds ¹ .
2010 - 2019	~20,000	~500,000	~80 Million	Increasing

				commercial payloads, minor fragmentation events, Briz-M explosion ² .
2020 - Present	~36,500	> 1,000,000	~130 Million	Rapid deployment of mega-constellations (Starlink, OneWeb), surging from 14,698 objects in 2015 to 34,595 by 2023 ¹ .

Table I: Referenced and modeled growth of orbital debris populations across operational size thresholds over the last three decades, demonstrating the exponential scaling of the space traffic environment¹.

The recent paradigm shift toward commercial satellite mega-constellations—such as SpaceX's Starlink, OneWeb, and Amazon's Project Kuiper—has saturated highly coveted orbital planes³. With forecasts predicting an average of 2,900 satellite launches annually over the next decade, the spatial density of LEO is increasing at an unprecedented rate³. This extreme density elevates the baseline Probability of Collision (PoC) to alarming levels. Consequently, operators are forced to implement highly conservative reaction thresholds—often reacting to risk probabilities of 10^{-4} or 10^{-5} —resulting in a drastic rise in required Collision Avoidance Maneuvers (CAMs)⁴. For operators of mega-constellations, this currently translates to an average of over a dozen maneuvers per satellite annually⁴. The sheer volume of these Conjunction Data Messages (CDMs) renders human-in-the-loop oversight and manual CAM planning economically and practically unsustainable, demanding an immediate transition toward autonomous, algorithmic Space Traffic Management (STM) frameworks².

C. Limitations of Traditional Tracking Algorithms and Analytical Models

The efficacy of Space Situational Awareness (SSA) relies entirely on the precision, timeliness, and predictive accuracy of object detection, orbit determination, and conjunction assessment. Ground-based infrastructure, comprising powerful phased-array radars and sophisticated optical telescopes, serves as the backbone of modern debris tracking. However, these traditional systems inherently suffer from critical physical and algorithmic limitations when attempting to monitor the 0.1 to 10 centimeter debris population³. Traditional radar tracking degrades rapidly with the inverse fourth power of distance, making small-cross-section debris practically invisible at higher altitudes, while optical systems are heavily constrained by illumination conditions, solar phase angles, and atmospheric distortion⁴.

When tracking data is successfully obtained, it is packaged into CDMs and distributed to satellite operators for risk assessment⁶. The mathematical and statistical models currently utilized to process these CDMs and compute the PoC—such as the widely adopted Alfriend-Akella formulation and the Foster-1992 method—rely on significant and increasingly precarious simplifications³. The Foster-1992 method, for instance, assumes that the relative velocity between two converging

objects is so high that the encounter duration is extremely short, allowing the relative motion to be approximated as purely rectilinear⁶. Furthermore, it assumes that the positional uncertainties of the primary and secondary objects are constant, uncorrelated, and conform strictly to Gaussian distributions during the encounter⁷.

While these linear approximations are computationally inexpensive and historically sufficient for sparse orbital environments, they break down severely over long-term encounters, curved relative trajectories, or when covariance geometries are highly anisotropic due to drag and solar radiation pressure⁴. Furthermore, traditional algorithms assess potential collisions in a static, isolated manner, failing to account for the temporal evolution of the debris cloud or the complex, non-linear progression of uncertainty covariances leading up to the Time of Closest Approach (TCA)². The lack of predictive generalization and the inability to quickly process the non-linear dynamics of faint, hypervelocity micro-debris underscore the absolute necessity for a technological leap in how optical SSA data is processed and interpreted.

II. BACKGROUND AND PROBLEM FORMULATION

A. Orbital Mechanics of Space Debris and Environmental Challenges in LEO

The orbital dynamics defining LEO are governed by high velocities and complex non-linear perturbations that make precise tracking and maneuvering extraordinarily difficult. More than 900,000 small debris objects measuring 1 centimeter or greater currently populate LEO in an uncontrolled state⁶. Encounters between spacecraft and this orbital debris are typically characterized by extreme relative velocities, often approximating 7 to 10 kilometers per second³. The motion of these objects is not purely Keplerian; it is significantly altered by atmospheric drag and the Earth's oblateness.

The drag force f_D encountered by an object in LEO extracts kinetic energy from the orbit. The time derivative of orbital energy due to this drag is linked to the inverse ballistic coefficient β^* and atmospheric density ρ , described by the relationship:

$$\dot{E} = \frac{\mu_E}{2a^2} \dot{a} = -\frac{1}{2} \beta^* \rho v^3$$

[cite: 2]

where a is the semi-major axis, v is the orbital velocity, and μ_E is the Earth's standard gravitational parameter. Furthermore, the J_2 perturbation—arising from Earth's equatorial bulge—induces secular variations in the Right Ascension of the Ascending Node (RAAN), quantified by the precession rate $\dot{\Omega}$:

$$\dot{\Omega} = -\frac{3}{2} J_2 \sqrt{\frac{\mu}{a^3}} \left(\frac{R_e}{a} \right)^2 \cos i$$

[cite:] where R_e is the equatorial radius of the Earth and i is the orbital inclination. These dynamic fluctuations force mission planners to rely heavily on precise, high-frequency Space Situational Awareness (SSA) updates to calculate orbital drift, collision windows, and necessary intervention windows accurately².

B. Mathematical Formulation of Collision Probability and Risk Assessment

The fundamental metric for orbital risk assessment is the Probability of Collision (PoC). When a potential encounter is detected, operators receive Conjunction Data Messages (CDMs) containing state vectors and covariance matrices representing the positional uncertainties of the objects involved⁶. The mathematical backbone of evaluating these CDMs

relies on the Foster-1992 method, which reduces the three-dimensional encounter to a two-dimensional probability integral evaluated on the B-plane—a plane orthogonal to the relative velocity vector at the Time of Closest Approach (TCA)².

By projecting the combined positional uncertainty (covariance) $C_{tot,B}$ of the two objects and sweeping the integration over the combined hard body radius R_C (the physical size threshold for a collision), the PoC is computed as:

$$P_c = \frac{1}{2\pi \sqrt{\det(C_{tot,B})}} \int_{-R_C}^{R_C} \int_{-\sqrt{R_C^2 - x_B^2}}^{\sqrt{R_C^2 - x_B^2}} \exp(-A_B) dy_B dx_B$$

where the exponent term representing the Mahalanobis distance is defined as:

$$A_B = \frac{1}{2} \Delta r_B^T C_{tot,B}^{-1} \Delta r_B$$

².

C. Sensing Modalities: Limitations in Complex Skylight and Low SNR

Because physical mitigation relies entirely on accurate TCA and PoC calculations, detecting the 1 mm to 10 cm debris population remains a foundational bottleneck. Ground-based phased-array radars degrade exponentially with altitude, relying instead on optical telescope arrays and space-based visual sensors⁶.

Optical sensing of space debris inherently struggles with capturing faint, fast-moving streaks. Debris targets frequently manifest as sub-pixel entities that reflect nominal amounts of solar illumination⁵. In unmanned aerial and space-based imagery, target objects often blend into complex skylight backgrounds defined by atmospheric scattering, stellar clutter, and severe sensor noise⁸. The resulting Signal-to-Noise Ratio (SNR) is exceptionally low, making these streaks visually negligible to traditional thresholding and background-subtraction filters⁹.

D. The Active Debris Removal (ADR) Transfer Problem

Once targets are verified via enhanced sensing, physically remediating the threat involves deploying an Orbital Transfer Vehicle (OTV) to conduct Active Debris Removal (ADR). This mission planning requires solving a dynamic Cost-Constrained Traveling Salesman Problem (CCTSP), where the goal is to sequence visits to multiple debris targets while

minimizing propellant (ΔV) expenditure and strictly adhering to operational time constraints.

The orbital maneuvers between targets depend on solving Lambert's problem or executing multi-impulse Hohmann transfers to match the precise Keplerian elements of each sequential target¹¹. The state transition dynamics iteratively update the OTV's remaining fuel and time post-

aneuver $\dot{\mathbf{z}}$:

$$s'[\Delta V_{left}] = s[\Delta V_{left}] - \Delta V_i$$

$$s'[\Delta T_{left}] = s[\Delta T_{left}] - \Delta T_i$$

[cite:].

III. LITERATURE REVIEW

A. Tracking and Computer Vision

Accurate surveillance of Low Earth Orbit (LEO) demands advanced algorithmic methodologies capable of functioning dynamically within severe constraints. Addressing the limitations of traditional tracking, the Space Debris Tracking Network (SDT-Net) has emerged as a groundbreaking deep learning-based framework tailored specifically for high-accuracy tracking in complex skylight backgrounds¹². Unlike traditional signal processing approaches that degrade under dense debris conditions, SDT-Net integrates a Region-of-Interest Feature Enhancement (RoIFE) module¹³. This module captures the intrinsic features of extremely faint linear streaks characteristic of long-exposure space observation. SDT-Net follows a tracking-by-detection paradigm where deep features are matched across continuous frames using endpoint association, achieving a Multiple Object Tracking Accuracy (MOTA) of 73.2% when tested on real Antarctic telescope data¹². To support SDT-Net, the Space Debris Tracking Dataset (SDTD) was curated from Zwicky Transient Facility (ZTF) images, using a specialized ZScale pre-processing method to standardize extreme pixel variances. The ZScale mapping translates raw pixel intensities $I(x, y)$ utilizing median z_{median} and standard deviation z_{std} boundaries:

$$I_{scaled}(x, y) = 255 \times \frac{I(x, y) - z_1}{z_2 - z_1}$$

where $z_{1,2} = z_{median} \pm k \times z_{std}$ ¹⁴.

Complementing pure computer vision, CosmosDSR offers an advanced methodology for the automated detection and multi-object orbit estimation of space debris by fusing YOLOv3 object detection with Unscented Kalman Filters (UKF)¹⁵. The YOLOv3 layer functions as an initial bounding-box regressor on optical frames. However, because traditional Extended Kalman Filters (EKF) suffer from extreme Jacobian approximation errors under the highly non-linear dynamics of orbital mechanics, CosmosDSR leverages the UKF. By deterministically sampling sigma points, the UKF captures the posterior mean and covariance accurately to the 3rd order of any non-linearity, offering vastly superior state prediction for hypervelocity debris¹⁵.

Shifting paradigms from spatial-visual tracking to material characterization, SpectraNet addresses the Unresolved Space Object (URSO) problem¹⁸. Utilizing a Deep Residual Learning (ResNet) architecture, SpectraNet bypasses visual pixel detection entirely by extracting features from Near-Infrared Spectroscopy (NIRS) data¹⁹. By learning the unique spectral signatures and thermal emissions of debris materials against the cosmic background, SpectraNet enables the classification and localization of non-reflective orbital debris that traditional CCDs fail to capture²¹.

B. Image Enhancement

Before detection networks can effectively operate, severe signal-to-noise ratio (SNR) deficits in aerial and astrophotography must be mitigated. The Hybrid UNet-ResNet34 architecture addresses this via pixel-level semantic segmentation and super-resolution reconstruction²³. The core innovation relies on integrating a ResNet-101 or ResNet-34 backbone into the encoder side of a traditional UNet²⁴. The ResNet blocks alleviate the vanishing gradient problem in deep feature extraction, capturing high-level global embeddings, while the symmetric UNet decoder utilizes dense skip connections to perfectly reconstruct the spatial morphology of faint debris streaks²³.

Furthermore, advancements tailored specifically for Unmanned Aerial Vehicle (UAV) and high-altitude optical sensors have been adapted for space. FCML-YOLO utilizes a Frequency-Domain Feature Enhancement (FDFE) module alongside a lightweight multi-level feature fusion architecture⁹. The FDFE relies on discrete cosine transforms to elevate high-frequency edge information—vital for faint streak boundaries—over low-frequency background scattering⁹. Similarly, YOLO-DBS leverages deformable convolutions (DCNv2) to adaptively alter the receptive field to match the varied, elongated shapes of

debris streaks, outperforming baseline models by 3.1% in mean Average Precision (mAP)²⁵.

C. Active Mitigation and Scheduling

The active mitigation phase relies heavily on Deep Reinforcement Learning (DRL) to adaptively solve the Cost-Constrained Traveling Salesman Problem (CCTSP). In contrast to static heuristics like Genetic Algorithms (GA) or Greedy Searches, DRL formulates the environment as a Markov Decision Process (MDP)⁵. Using Masked Proximal Policy Optimization (PPO), an Orbital Transfer Vehicle (OTV) learns amortized policies for sequential debris targeting⁷.

The state space $\mathbf{s}_t$ fed to the PPO network comprises the spacecraft's remaining fuel (ΔV_{left}), current Cartesian coordinates, and dynamic collision risk vectors corresponding to unvisited debris targets⁵. The action space $\mathcal{A}$ dictates the next target selection or immediate Collision Avoidance Maneuver (CAM) execution. The objective is optimized via a clipped surrogate loss function:

$$L^{CLIP}(\theta) = \mathbb{E}_t \left[\min \left(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t \right) \right]$$

where $\hat{A}_t$ is the advantage estimate⁷. The reward function r_t severely penalizes time and fuel depletion while incentivizing successful rendezvous (δ_{visit}) and penalizing collisions (C_t):

$$r_t = \delta_{visit} - C_t - T_{penalty}$$

To ensure physical feasibility during mission sequencing, invalid action masking filters out mathematically impossible orbital transfer targets directly from the policy's softmax layer, accelerating convergence⁵. PPO networks applied to this problem have demonstrated a 13.66% reduction in mission completion time compared to greedy heuristics, while autonomously negotiating $5 \times 5 \times 5$ kilometer dynamically spawning collision zones⁵.

Comparative Analysis of Tracking and Enhancement Architectures

Model Architecture	Base Framework	Primary Application	Key Datasets Evaluated	Complexity / Performance Metrics
SDT-Net	Tracking-by-Detection (CenterTrack)	Optical Streak Tracking	SDTD, ZTF Antarctic Data	High; Achieves 73.2% MOTA on real telescopic data ¹² .
CosmosDSR	YOLOv3 + UKF Fusion	Kinematic Orbit Estimation	Custom Astrodynamics Sets	Very High; Computationally expensive due to continuous UKF covariance

				updates ¹⁵ .
SpectraNet	ResNet-53	Spectral Material Classification	NIRS, URSO spectral catalogs	Medium; Eliminates pixel-level background noise dependencies ¹⁹ .
YOLO-DBS	YOLOv8 + DCNv2	Low-SNR Image Enhancement	RUOD, Submerged Debris	Low; 32% parameter reduction relative to YOLOv8n, +3.1% mAP@0.5 ²⁵ .

IV. PROPOSED UNIFIED ALGORITHMIC FRAMEWORK

To bridge the gap between Space Situational Awareness (SSA) and Active Debris Removal (ADR), we propose a unified, end-to-end algorithmic pipeline that systematically processes raw telemetry and translates it into actionable astrodynamical maneuvers.

1. Stage 1: Raw Optical Capture and Pre-Processing: Space-based and ground-based optical sensors capture raw, cluttered imagery. The ZScale algorithm normalizes severe illumination variations induced by the sun's phase angle against the stellar background.
2. Stage 2: Hybrid Feature Enhancement: The normalized image is passed into the UNet-ResNet34 semantic segmenter. Utilizing Frequency-Domain Feature Enhancement (FDfE), high-frequency streak edges are isolated while low-frequency cosmic noise is computationally suppressed.
3. Stage 3: Detection and Kinematic Filtering: The enhanced frames are fed into SDT-Net. Utilizing the RoIFE module, the network detects elongated streak endpoints. These raw positional vectors are then processed by the CosmosDSR UKF module, which translates 2D pixel velocities into 3D Keplerian state vectors and generates the associated uncertainty covariance matrices.
4. Stage 4: DRL Mission Sequencing: The updated Keplerian states and risk probabilities are pushed to the on-board OTV computer. The Masked PPO agent evaluates the current state space (fuel, time, dynamic risks) and selects the optimal sequential target. If a $5 \times 5 \times 5$ km collision zone spawns along the nominal Hohmann transfer arc, the agent autonomously injects a CA Above or CA Below elliptical detour maneuver.
5. Stage 5: Execution and Iteration: The OTV executes the calculated ΔV burn. The environment state is iteratively updated, resetting the policy loop until total mission completion or resource depletion.

V. PERFORMANCE METRICS AND DATA VISUALIZATION

Evaluating the proposed algorithms requires rigorous statistical metrics. Object tracking performance relies heavily on MOTA (Multiple Object Tracking Accuracy), which aggregates false positives, false negatives, and identity switches across all video frames. Orbital state prediction accuracy is measured using Root Mean Square Error (RMSE) between the UKF-predicted trajectory and the ground truth. Finally, the reinforcement learning agent is evaluated on the Cumulative Episodic Reward, highlighting the model's convergence stability.

Below are three advanced Python code implementations utilizing matplotlib and seaborn to generate synthetic graphs modeled after the data presented in the literature⁷.

Python

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Synthetic data mimicking tracking accuracy over time/epochs
epochs = np.arange(1, 101, 5)
yolo_mota = 45.0 + 15.0 * (1 - np.exp(-0.05 * epochs)) + np.random.normal(0, 1.5, len(epochs))
sdt_net_mota = 50.0 + 23.2 * (1 - np.exp(-0.08 * epochs)) + np.random.normal(0, 1.0, len(epochs))

sns.set_theme(style="whitegrid")
plt.figure(figsize=(10, 6))
plt.plot(epochs, sdt_net_mota, label='SDT-Net', color='darkblue', linewidth=2.5, marker='o')
plt.plot(epochs, yolo_mota, label='Standard YOLOv3', color='crimson', linestyle='--', linewidth=2, marker='s')

plt.title('MOTA Tracking Performance: SDT-Net vs Baseline YOLOv3', fontsize=14, fontweight='bold')
plt.xlabel('Training Epochs', fontsize=12)
plt.ylabel('Multiple Object Tracking Accuracy (MOTA) %', fontsize=12)
plt.legend(loc='lower right', fontsize=11)
plt.axhline(73.2, color='green', linestyle=':', label='Real-world Benchmark (73.2%)')
plt.grid(True, linestyle='solid')
plt.show()
```

Python

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Synthetic data mimicking tracking error (RMSE) over propagation distance
distances_km = np.linspace(100, 5000, 20)
ekf_rmse = 0.5 * (distances_km / 100) ** 1.3 + np.random.normal(0, 5, len(distances_km))
ukf_rmse = 0.5 * (distances_km / 100) ** 1.1 + np.random.normal(0, 2, len(distances_km))

plt.figure(figsize=(10, 6))
plt.fill_between(distances_km, ekf_rmse - 8, ekf_rmse + 8, color='red', alpha=0.1)
plt.plot(distances_km, ekf_rmse, label='Extended Kalman Filter (EKF)', color='red', linewidth=2)

plt.fill_between(distances_km, ukf_rmse - 3, ukf_rmse + 3, color='blue', alpha=0.2)
plt.plot(distances_km, ukf_rmse, label='CosmosDSR Unscented Kalman Filter (UKF)', color='blue', linewidth=2.5)

plt.title('Orbital State Prediction Error over Transfer Distance', fontsize=14, fontweight='bold')
plt.xlabel('Target Distance (km)', fontsize=12)
plt.ylabel('Positional RMSE (m)', fontsize=12)
plt.legend(loc='upper left', fontsize=11)
plt.grid(True, layout='loose')
# plt.show()
```

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

# Synthetic data mimicking DRL Episodic Reward Convergence
episodes = np.linspace(0, 1e6, 200)
greedy_reward = np.ones_like(episodes) * 0.5
dqn_reward = 1.2 - 1.0 * (1 - np.exp(-3e-6 * episodes)) + np.random.normal(0, 0.1, len(episodes))
ppo_reward = 1.4 - 1.5 * (1 - np.exp(-5e-6 * episodes)) + np.random.normal(0, 0.05, len(episodes))

plt.figure(figsize=(10, 6))
sns.lineplot(x=episodes, y=ppo_reward, label='Masked PPO Agent', color='teal', linewidth=1.5)
sns.lineplot(x=episodes, y=dqn_reward, label='DQN Agent', color='orange', alpha=0.7)
plt.plot(episodes, greedy_reward, label='Greedy Heuristic Baseline', color='black', linestyle='--')

plt.title('Reinforcement Learning Convergence for ADR Sequencing', fontsize=14, fontweight='bold')
plt.xlabel('Training Episodes', fontsize=12)
plt.ylabel('Cumulative Episodic Reward', fontsize=12)
plt.legend(loc='lower right', fontsize=11)
plt.grid(True, layout='tight')
# plt.show()
```

VI. FUTURE SCOPE

While deep reinforcement learning and advanced computer vision represent significant milestones in space debris tracking and mitigation, future research must pivot toward next-generation computational hardware and coordinated swarm robotics. Classical multi-target ADR scheduling formulated as a Cost-Constrained Traveling Salesman Problem (CCTSP) becomes computationally intractable for classical Von Neumann architectures as the dataset scales into the hundreds of potential targets. Quantum Annealing (QA), utilizing adiabatic quantum computation paradigms, has demonstrated profound potential in resolving the combinatorial explosions inherent to ADR routing². By formulating the ADR sequence optimization as a Quadratic Unconstrained Binary Optimization (QUBO) problem, D-Wave Quantum Processing Units (QPUs) map the total propellant cost onto a Hamiltonian energy landscape². The Hamiltonian objective function is expressed as:

$$H = \sum_{i=0}^{N_t} \sum_{j=0}^{N_t} x_{i,j} (C_{i,j} + C_i)$$

where $x_{i,j}$ represents the binary decision variable of transferring from debris i to j , $C_{i,j}$ is the transfer cost, and C_i is the deorbit cost². Quantum-classical hybrid algorithms utilizing hardware like the D-Wave Advantage QPU have empirically solved dense 79-target sequences (requiring 6,478 binary variables) in approximately 25 seconds of QPU access time, vastly outperforming Tabu Search and Simulated Annealing metaheuristics².

Concurrently, the physical mitigation aspect must evolve beyond singular, monolithic Orbital Transfer Vehicles. The deployment of NanoTug Swarms—coordinated fleets of nanosatellites executing multi-agent cooperative capture—will drastically reduce individual launch costs. These swarms will rely on decentralized Multi-Agent Reinforcement Learning (MARL) policies, operating collaboratively to attach dragging tethers or electrodynamic braking systems to massive debris clusters simultaneously.

VII. CONCLUSION

The exponential proliferation of space debris and satellite mega-constellations strictly necessitates the modernization of Space Traffic Management away from human-in-the-loop manual assessments towards fully autonomous, AI-driven architectures. This paper has comprehensively analyzed the algorithmic frontier of space sustainability. By deploying advanced Convolutional Neural Networks (UNet-ResNet34) alongside deformable convolution modules (YOLO-DBS) and tracking-by-detection frameworks (SDT-Net), optical observation systems can now isolate and track hypervelocity, low-SNR micro-debris that previously evaded traditional radar and photometric models. Furthermore, modeling Active Debris Removal as a Markov Decision Process solved via Masked Proximal Policy Optimization transforms static, heuristic-based mission planning into a dynamic, adaptive framework capable of optimizing fuel expenditure while autonomously dodging dynamically manifesting collision zones. Moving forward, the fusion of these deep learning models with Quantum Annealing for route optimization and NanoTug swarms for physical capture will ultimately dictate the long-term viability and safety of the Low Earth Orbit environment.

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