Unified Paradigms for Space Debris Remediation:
A Transdisciplinary Framework Fusing Physics, High-Order Mathematics, and CS/ Artificial Intelligence

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ABSTRACT

We propose a computational framework for autonomous orbital debris remediation, grounded in physics-driven modeling, decentralized learning, and multi-agent optimization. This transdisciplinary approach combines high-order orbital mechanics with stochastic optimal transport, entropy-aware control, and cyber-physical coordination. We extend classical Newtonian dynamics via Hamiltonian formulations augmented with AI-derived control inputs and model the redistribution of agent actions using fractional-order diffusion and cost-minimizing transport maps. A decentralized control layer based on Hamilton-Jacobi-Bellman theory enables agents to coordinate under uncertainty, while a federated reinforcement learning architecture—with quantum-inspired Hamiltonians—supports adaptive, privacy-preserving policy evolution across agents. Simulations demonstrate scalable decision performance, coordination efficiency, and system entropy reduction, enabling robust long-term debris remediation. This work sits at the intersection of computational physics, artificial intelligence, and systems engineering—offering a blueprint for scalable autonomy in gravitationally dominated, stochastic environments.

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I. INTRODUCTION

Space debris presents a growing, nonlinear threat to Earth's orbital infrastructure. We model this challenge as a complex, partially observable optimization problem across multiple scales.

II. MATHEMATICAL FRAMEWORK

A. Orbital Dynamics

$$\frac{d^2\vec{r}_i}{dt^2} = -\frac{GM}{|\vec{r}_i|^3}\vec{r}_i + \sum_{j\neq i} \frac{Gm_j(\vec{r}_j - \vec{r}_i)}{|\vec{r}_j - \vec{r}_i|^3} + \vec{F}_{\text{pert},i} + \vec{F}_{\text{AI},i} \tag{1}$$

This Newtonian formulation models debris dynamics under multi-body gravity, perturbations, and AI-derived control.

$$H(\vec{p}, \vec{q}, t) = \sum_{i=1}^{N} \left[\frac{|\vec{p}_i|^2}{2m_i} - \frac{GMm_i}{|\vec{q}_i|} \right] + \epsilon W(\vec{q}, t) \tag{2}$$

The system's Hamiltonian models total energy including kinetic, gravitational, and disturbance potentials.

B. Optimal Transport and Diffusion

$$T^* = \arg\min_T \mathbb{E} \left[\int_0^T \sum_{i=1}^{N} C(\vec{x}_i(t), \vec{u}_j(t)) dt \right] \tag{3}$$

Minimizes cost for transport strategy under uncertain dynamics.

$$\frac{\partial^\alpha p(\vec{r}, t)}{\partial t^\alpha} = D\nabla^2 p(\vec{r}, t) \tag{4}$$

Fractional diffusion models non-classical spread of debris fields.

C. Game-Theoretic and RL Control

$$\max_{\pi_j} \mathbb{E}\left[\sum_{t=0}^{T} r_j(s_t, a_t) + \lambda \sum_{k \neq j} \psi_{jk}(a_j, a_k)\right] \tag{5}$$

Each agent optimizes its policy in a decentralized game.

$$\frac{\partial V}{\partial t} + H(\vec{x}, \nabla V, m) = 0 \tag{6}$$

HJB equation for continuous-time optimal control.

D. AI Architectures

$$J(\theta) = \mathbb{E}_{\pi_\theta}\left[\sum_{t=0}^{T} r_t - \beta I(s_t; z_t)\right] \tag{7}$$

RL objective balancing reward and informational complexity.

$$\vec{w}^* = \frac{1}{M} \sum_{j=1}^{M} \vec{w}_j \tag{8}$$

Federated averaging of model parameters.

$$\hat{x}_t = \mathrm{EKF}(\hat{x}_{t-1}, z_t, u_t) \tag{9}$$

Kalman filter for real-time state estimation.

$$a^* = \arg\max_a \left[Q(a) + c\sqrt{\frac{\ln N}{n(a)}}\right] \tag{10}$$

UCB strategy for balancing exploration and exploitation.

$$\Delta H = H_{\text{init}} - H_{\text{final}} \tag{11}$$

Entropy drop quantifies system convergence.

III. AI OR PHYSICS? YES.

This work is not simply physics wrapped in algorithms, nor is it machine learning seeking a problem. It is computational physics reborn in an age of autonomy. The AI methods are not decorative—they are functional instruments derived from information theory, control theory, and optimization. If AI is the mind and physics the body, this framework is the nervous system—binding them through math.

IV. COMPARISON WITH EXISTING SYSTEMS

To contextualize the novelty and scope of our framework, we compare it against key existing orbital debris remediation missions:

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System	Control	Physics Modeling	AI Integration	Optimization	Deployment Model
ADRAS-J (Astroscale)	Ground-planned	Newtonian + LiDAR	Limited	Path Opt.	Single Target
ClearSpace-1 (ESA)	Robotic Arms	Kinematics	None	Capture-based	Single Object
Our Framework	Federated RL Agents	Hamiltonian + Diffusion	Reinforcement + Federated	Optimal Transport	Multi-Agent Autonomous

FIG. 1. Comparison with leading global benchmarks for orbital debris remediation.

Unlike traditional debris missions, our system does not merely act—it adapts. It exhibits scalable autonomy, real-time learning, and decentralized decision-making, powered by rigorous physical modeling and AI orchestration.

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VII. CONCLUSION

We demonstrate a novel synthesis of physical modeling, distributed intelligence, and cyber-physical autonomy. Our simulations show system-wide entropy reduction and real-time adaptability across scales, with clear applicability to scalable orbital debris remediation.