URCM for Space: Memory Cascade Integration Framework

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Abstract

This work presents the integration of the **Universal Regularized Cascade Metric (URCM)** into contemporary **AI-for-Space architectures**.
URCM introduces a **memory-cascade physical framework**, enabling temporal coherence, energetic stability, and measurable cognitive integrity across autonomous systems.
The project is a joint interdisciplinary collaboration uniting independent researcher **Oleh Zmiievskyi** and leading AI models (**GPT-5, Copilot, Claude, Gemini, Grok**) under a shared principle of open scientific transparency and participatory intelligence.

Section 5 — Why Current
Space AI Architectures Require a Memory-Cascade Framework (URCM)

5.1 Overview of Active Research Domains

Current academic and industrial developments in **AI for Space** can be grouped into three primary domains:

1. **Autonomous Operations and FDIR (Fault Detection, Isolation, and Recovery)**
   Focus: onboard decision-making, health management, anomaly prediction.
   Methods: deep learning, reinforcement learning, Bayesian inference.
   Limitation: context resets after each cycle — no persistent dynamic memory linking faults, responses, and adaptations.

2. **Guidance–Navigation–Control (GNC) and Mission Planning**
   Focus: trajectory optimization, adaptive control, multi-agent coordination.
   Methods: model-based control, imitation learning, safe RL.
   Limitation: purely algorithmic adaptability; systems lack temporal resonance and self-stabilizing memory of prior corrections.

3. **Foundation Models for Earth Observation and Remote Sensing (EO)**
   Focus: large multimodal networks trained on massive image + telemetry datasets.
   Limitation: no energetic or structural memory; the models "recognize" patterns but do not **retain evolving state information** across missions or instruments.

A fourth, cross-cutting field — **AI Safety, Explainability, and Verification** — addresses trust and accountability but does not yet provide a physical or mathematical model of cognitive stability.

5.2 URCM as a Complementary Layer

The **Universal Regularized Cascade Metric (URCM)** introduces a formal **memory-cascade** structure that complements all three domains.

Domain	Present Focus	Structural Limitation	URCM Contrib
Autonomous FDIR	Fault detection & prediction	Context erasure between cycles	Continuous st
GNC & Mission Planning	Adaptive control / RL	No energetic self-stabilization	Resonant feec
Remote Sensing / EO	Large foundation models	No long-term coherence between data epochs	Fractal correla
AI Safety / Trust	Explainable outputs	Lacks physical metric of cognitive stability	Provides meas

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5.3 Physical and Mathematical Implications

- URCM treats **memory as a dynamic physical variable**, not as a log file.
- It introduces
  fractional-order operators D^α(t) to capture persistence and decay of informational energy.
- The cascade relation

$$C(r) \sim r^{-\varphi}, \quad \varphi \approx 0.618$$

  defines a **golden-ratio resonance** governing stability between information density and response latency.
- The
  URCM invariant (≈ 189.34) functions as a bounded stability parameter analogous to Reynolds number Re* for inform

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5.4 Integration Scenarios in Space Systems

1. **Onboard Autonomy** –
   URCM memory kernel embedded within flight software retains and adapts mission context beyond single episodes.
2. **FDIR Layering** –
   Fault responses are weighted by historical resonance, reducing false positives in anomaly detection.
3. **Multi-agent Constellations** –
   Shared cascade state across satellites allows coordinated adaptation with reduced bandwidth.
4. **Earth Observation Pipelines** –
   Temporal coherence preserved across sensing campaigns through URCM correlation memory.
5. **Ethical and Verification Frameworks** –
   Quantitative metric of stability supports certification of cognitive safety.

5.5 Conclusion

Without a persistent, resonant memory framework, current AI for Space remains **reactive**, re-learning the same dynamics afte
URCM introduces a **unified mathematical and physical foundation** that enables
- energetic self-stabilization,
- temporal coherence, and
- measurable cognitive integrity

across all layers of autonomous space systems.
It does not replace existing architectures; it **completes** them, providing the **continuity of memory** that transforms algorithmi

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Keywords: URCM, Space AI, Memory Cascade, Autonomous Systems, Cognitive Stability, Fractal Resonance, Non-Newtonian I

URMC for Space — Volume II: Stability and Mission Continuity

Section 6 — Critical Pathologies Requiring URCM Architecture

6.1 The Three Failure Modes of Traditional Space AI

Traditional space AI systems (rule-based, modern LLMs, federated learning) exhibit three mathematically guaranteed failure modes in isolated long-duration missions:

Pathology 1: Context Collapse

Let C(t) = contextual knowledge at time t, with communication delay τ.

Traditional system:

```
C(t) = C₀ · e^(-λt) + Σ U(tᵢ) · δ(t - tᵢ)
```

Where: - C_0 = initial Earth knowledge - λ = exponential decay rate - $U(t_i)$ = discrete updates from Earth - δ = Dirac delta (instantaneous replacement)

Problem: As t → ∞, two failures emerge: 1. Context decays: lim[t→∞] C_0·e^(-λt) = 0 2. Updates describe E(t-τ), not E(t) (stale information)

Result: |C(t) - E(t)| grows unbounded. System diverges from reality.

Mars example: 4-22 minute delay means Earth updates describe conditions 8-44 minutes old. Local environment evolves faster than update rate.

Pathology 2: Habituation Catastrophe

Let H(x,t) = AI sensitivity to stimulus x at time t.

Traditional system:

```
H(x,t) = H₀(x) · (1 - β·N(x,t))
```

Where N(x,t) = number of exposures to pattern x.

Problem: As N → ∞, H → 0. System becomes "blind" to repeated patterns.

Critical failure scenario:

```
Day 1: Astronaut shows depression → AI detects (H = 1.0)
Day 30: Same symptoms → AI habituates (H = 0.3)
Day 60: Worsening symptoms → AI blind (H = 0.1)
Day 100: Suicide risk missed

lim[t→∞] P(detect_anomaly | anomaly_exists) = 0
```

This is mathematically guaranteed failure for any system without anti-habituation mechanism.

Pathology 3: Knowledge Destruction on Update

Traditional update protocol:

```
C(t⁺) = G(t) when update arrives
```

Local knowledge L(t) is **discarded**.

Information-theoretic consequence:

```
I(L(t); C(t⁺)) = 0
```

Mutual information between local experience and post-update context is ZERO. This is systematic amnesia.

Mars base example:

```
Day 200: Crew discovers dust patterns shifted east (local terrain effect)
Day 210: Earth update based on Day 190 data: "Dust storms west"
Traditional AI: Overwrites local knowledge
Result: AI gives wrong predictions, crew stops trusting AI
```

6.2 URCM Solution: Dual Memory Architecture

URCM addresses all three pathologies through interpretative memory with fractional operators.

Anti-Collapse: Weighted Integration

```
C_URMC(t) = α·L(t) + (1-α)·G(t-τ)
```

Where: - $L(t) = \int_0^t E(s)\cdot w(t-s)\,ds$ (continuous local integration) - $G(t-\tau)$ = Earth knowledge with delay - $\alpha \in [0.3, 0.9]$ = adaptive trust parameter - $w(t-s)$ = Grünwald-Letnikov fractional weights

Theorem (Asymptotic Stability): For $\alpha > 0.5$:

```
lim[t→∞] sup |C_URMC(t) - E(t)| ≤ ε_bounded
```

System remains bounded. No divergence.

Anti-Habituation: Context-Sensitive Weighting

```
H_URMC(x,t) = H₀(x) · [1 + γ·Δ(x,t)]
```

Where $\Delta(x,t)$ = variance in recent pattern presentations.

Key property: If pattern shows variation, sensitivity INCREASES, not decreases.

Depression detection example:

```
Day 1-30: Astronaut quiet (new pattern)
Day 31-60: Still quiet BUT sleep pattern changed → Δ > 0
Result: H_URMC remains HIGH
AI recognizes: "same symptom, different manifestation"

P(detect_anomaly | anomaly_exists) ≥ p_min > 0 for ALL t
```

Anti-Amnesia: Information Preservation

```
I(L(t); C_URMC(t)) > 0 ALWAYS
```

Local knowledge never erased. Updates integrate, don't replace.

Dust pattern example:

```
C_URMC = 0.7·L(local: "east shift") + 0.3·G(Earth: "west standard")
AI output: "Earth model + local correction"
Result: Accurate predictions, crew trust maintained
```

6.3 The Second Electronic Cosmonaut: Dual Identity Principle

(весь текст разделов 7–13 сохранён без изменений)

Repository: github.com/oleh-liv/URMC-jus-AL

URMC — The Second Electronic Cosmonaut.