Title Bamboo GPU Mode: A Game-Theoretic Evolutionary Framework for Resilient Self-Healing Navigation in Extreme Mars DEM Environments

Abstract Traditional autonomous navigation systems for planetary rovers, such as A* or Dynamic Window Approach (DWA), frequently experience irreversible failure in extraterrestrial environments due to extreme sensor noise (e.g., dust storms) and unpredictable terrain features (e.g., sand traps). This paper proposes **Bamboo GPU Mode**, a novel resilience-oriented framework that prioritizes system recovery over conventional path optimization.

The methodology integrates a **game-theoretic payoff matrix** with a **phototropic mutation** mechanism, modeling navigation as a population-based evolutionary process among virtual agents representing possible states. System health is quantified by a **Resilience Index** (R R R):

```
R=∫tcrashtrecoveryShareH(t)Dsys(t) dtR =
\int_{t_{\text{crash}}}^{t_{\text{recovery}}}
\frac{\text{Share}_H(t)}{D_{\text{sys}}(t)} \,
dtR=∫tcrash  trecovery    Dsys  (t)ShareH  (t)  dt
```

where ShareH(t) \text{Share}_H(t) ShareH (t) denotes the harmony/coordination score (0 to 1.0), and Dsys(t) D_{\text{sys}}(t) Dsys (t) represents the aggregate disturbance (noise + terrain complexity). GPU-accelerated parallel iteration (leveraging MPI-style distribution up to 1280 processes) ensures real-time execution on resource-constrained edge hardware, such as the NVIDIA Jetson Orin Nano.

High-fidelity simulations on synthetic Mars Digital Elevation Models (DEM) demonstrate **100% revival success rate** in 20 forced-crash pressure tests. Even under severe sensor degradation (σ=0.6 \sigma = 0.6 σ=0.6, simulating heavy dust storm conditions), the system reliably re-establishes an optimal coordinated state (ShareH=1.0 \text{Share}_H = 1.0 ShareH =1.0).

Bamboo GPU Mode offers a promising self-healing paradigm for future deep-space missions (e.g., Artemis lunar operations and ExoMars Rosalind Franklin rover), where mission survivability outweighs short-term optimality in highly uncertain environments.

1. Introduction

- **The Problem** : In planetary exploration, rovers often encounter catastrophic failures—such as entrapment in sand pits or complete sensor blackout during dust storms—that lead to mission termination. Conventional reactive planners (e.g., A*, D*) rely on deterministic assumptions and lack inherent mechanisms for post-failure recovery, resulting in high vulnerability in unstructured extraterrestrial terrains.

- **The Inspiration** : Drawing from the mechanical resilience of bamboo, which bends under extreme pressure yet spontaneously rebounds due to its internal dynamics, this work seeks to imbue robotic navigation systems with analogous self-restorative properties.
- **The Innovation** : We introduce the first framework that synergistically combines game-theoretic Nash equilibrium stability (via a parameterized payoff matrix) with evolutionary survival selection (via phototropic mutation), explicitly optimized for GPU parallel computing to achieve real-time self-healing on space-grade hardware.

2. Theoretical Framework

2.1 The Payoff Function Each virtual agent i i i evaluates its survival prospects in the current terrain state via a payoff function:

fi=C· eff(di,Dsys)−β(di−Dsys)2−αdif_i = C \cdot \text{eff}(d_i, D_{\text{sys}}) - \beta (d_i - D_{\text{sys}})^2 - \alpha d_ifi =C· eff(di ,Dsys)−β(di −Dsys)2−αdi

where:

- C C C is a constant scaling the baseline survival benefit,
- eff(di,Dsys) ¥text{eff}(d_i, D_{¥text{sys}}) eff(di ,Dsys) is an efficiency term reflecting alignment with system-wide disturbance,
- β ¥beta β penalizes deviation from the global disturbance level Dsys D_{¥text{sys}} Dsys (promoting coordination),
- α ¥alpha α applies a linear cost to individual displacement di d_i di .

This quadratic penalty structure encourages convergence toward a Nash equilibrium, where no agent benefits from unilateral deviation, thereby stabilizing collective navigation decisions under noise.

2.2 Phototropic Mutation Upon catastrophic failure (system crash detection), the framework triggers a directed mutational bias inspired by plant phototropism—growth toward light as a metaphor for seeking optimal states amid adversity:

dnew=dold+Δm(ϵ),ϵ=+0.05+N(0,σmut)d_{\text{new}} = d_{\text{old}} + \Delta m(\epsilon), \quad \epsilon = +0.05 + \mathcal{N}(0, \sigma_{\text{mut}})dnew =dold +Δm(ϵ),ϵ=+0.05+N(0,σmut)

The small positive bias **+0.05** serves as the core “restorative impulse,” systematically nudging agents toward higher-payoff configurations rather than pure randomness. This directed perturbation, combined with GPU-parallel evaluation of mutation offspring, enables rapid exploration and convergence to a recovered state (ShareH→1.0 \text{Share}_H \to 1.0 ShareH →1.0) in few iterations.