Evolutionary foraging in grids: Intermittent search dynamics emerge in finite, depletable landscapes

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NEURAL INFORMATION PROCESSING SYSTEMS
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1 Landscapes and trajectories

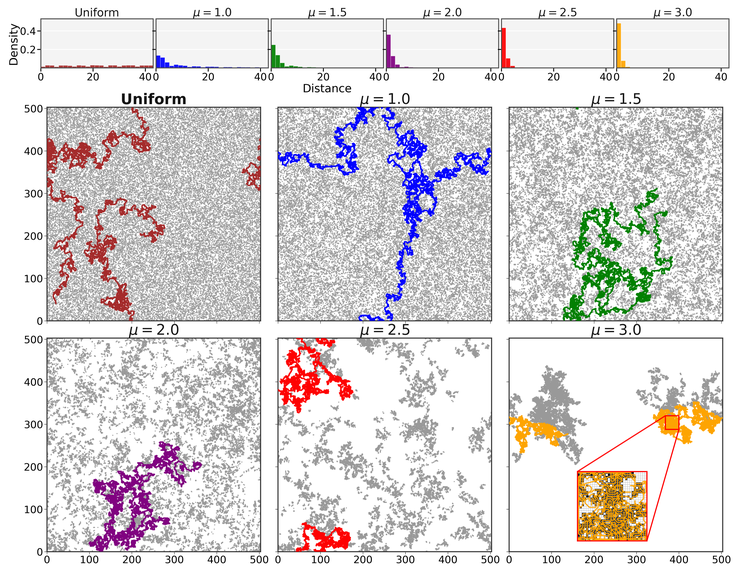


Figure 1. Uniform resources and five Lévy-dust fields. Gray: resources; color: evolved trajectories. $L = 503$, nominal $\rho = 0.15$.

Evolutionary search and fitness

3×30	40×1500	8000
Genome entries length, speed, angle	Agents × generations selection and mutation	Movement updates $p_{\text{cue}} = 0.5$

Fitness-proportionate selection with elitism, recombination, and bounded Gaussian mutation. No prescribed movement-distribution family.

ENERGY EFFICIENCY × COVERAGE EFFICIENCY

$$\mathcal{F}(t) = \frac{E_{\text{res}}(t)}{E_{\text{res}}(t) + Q(t)} \cdot \frac{N(t)}{N(t) + R(t)}$$

$$Q(t) = c_{\text{move}} \sum_{j=1}^{t} \Delta_j, \quad E_{\text{res}}(t) = \varepsilon n_{\text{res}}(t).$$

N: distinct sites; R: revisits. Resources are depleted at move endpoints; movement wraps on the torus.

Optimization pressure

The energy term balances collected resources against movement cost; the coverage term rewards visits to new sites relative to revisits.

2 Fitness and evolved movement

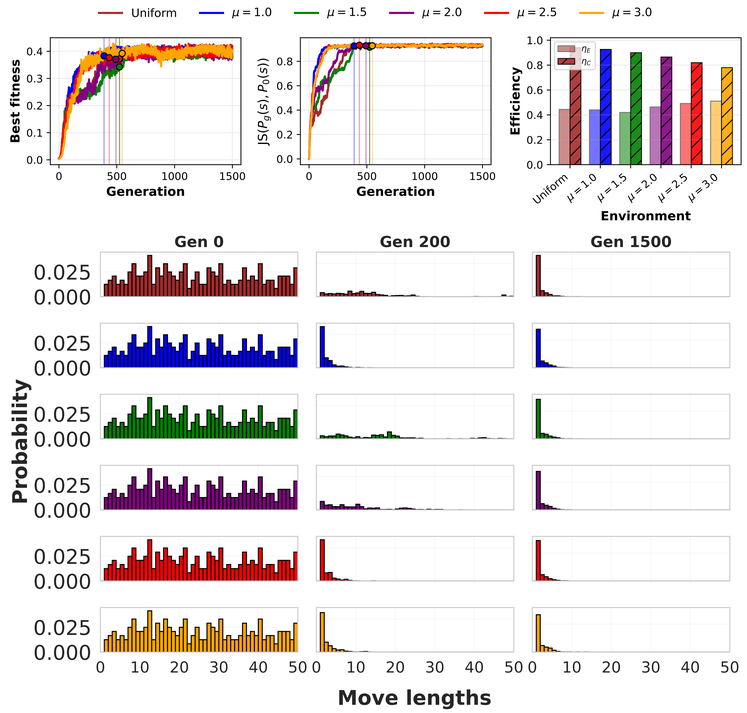


Figure 2. Fitness approaches a fluctuating plateau. By generation 200, the encoded step-length pool favors short entries while retaining a sparse longer-step tail. Shading: standard errors across agents within one run.

4 Model comparison

If $\Gamma = \bar{R}^2_{\text{IS}} - \bar{R}^2_{\text{LW}} > 0$, IS is chosen; o.w. LW is chosen.

Grid	Environments	Γ	$\bar{R}^2_{\text{IS}}$	$\bar{R}^2_{\text{LW}}$
211×211	Uniform	0.028 ± 0.004	0.9985 ± 0.0004	0.970 ± 0.004
	$\mu = 1.0$	0.019 ± 0.002	0.9984 ± 0.0002	0.980 ± 0.002
	$\mu = 1.5$	0.022 ± 0.003	0.9981 ± 0.0003	0.976 ± 0.003
	$\mu = 2.0$	0.024 ± 0.005	0.9993 ± 0.0002	0.975 ± 0.005
	$\mu = 2.5$	0.030 ± 0.007	0.9987 ± 0.0005	0.969 ± 0.007
	$\mu = 3.0$	$\mathbf{0.08 \pm 0.02}$	0.9986 ± 0.0006	0.92 ± 0.02
503×503	Uniform	0.017 ± 0.002	0.9983 ± 0.0004	0.982 ± 0.002
	$\mu = 1.0$	0.015 ± 0.005	0.9986 ± 0.0004	0.984 ± 0.005
	$\mu = 1.5$	0.018 ± 0.006	0.9987 ± 0.0004	0.981 ± 0.006
	$\mu = 2.0$	0.030 ± 0.002	0.9991 ± 0.0002	0.969 ± 0.002
	$\mu = 2.5$	0.04 ± 0.01	0.9992 ± 0.0002	0.960 ± 0.009
	$\mu = 3.0$	$\mathbf{0.08 \pm 0.03}$	0.9991 ± 0.0002	0.92 ± 0.03
1009×1009	Uniform	0.017 ± 0.001	0.9983 ± 0.0003	0.981 ± 0.001
	$\mu = 1.0$	0.019 ± 0.001	0.9985 ± 0.0002	0.979 ± 0.001
	$\mu = 1.5$	0.022 ± 0.006	0.9987 ± 0.0006	0.977 ± 0.006
	$\mu = 2.0$	0.031 ± 0.005	0.9992 ± 0.0003	0.968 ± 0.004
	$\mu = 2.5$	0.06 ± 0.02	0.9993 ± 0.0002	0.94 ± 0.02
	$\mu = 3.0$	$\mathbf{0.11 \pm 0.04}$	0.9990 ± 0.0006	0.89 ± 0.04

Mean ± SD. Five runs at $L = 503$; one run otherwise. Final 500 best-agent trajectories per run.

3 Displacement-moment fits

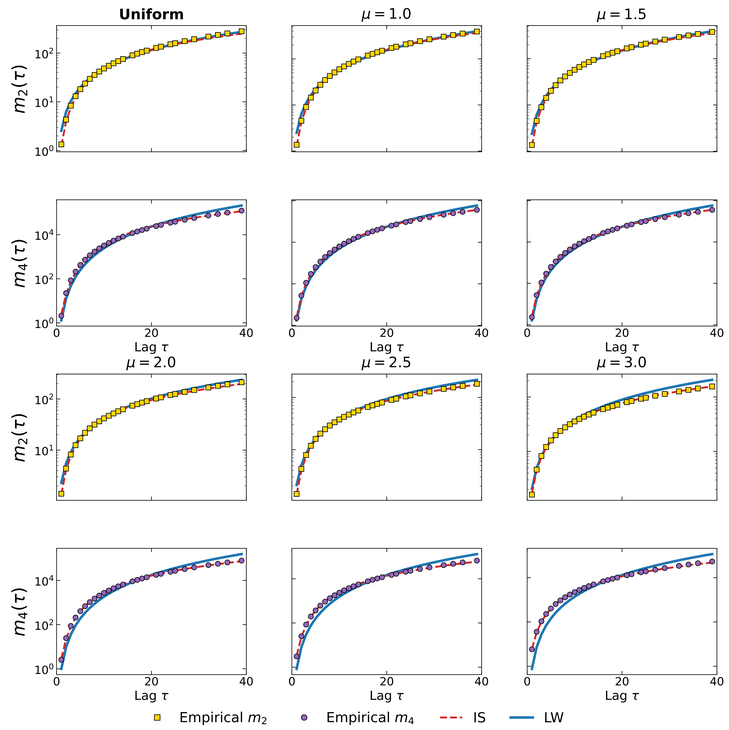


Figure 3. Second- and fourth-order displacement-moment fits at 28 lags ($L = 503$). IS: four parameters; LW: three.

$$m_k^{\text{obs}}(\tau) = \left\langle \|\mathbf{r}(t+\tau) - \mathbf{r}(t)\|^k \right\rangle_t, \quad k = 2, 4$$

$$\mathcal{J} = \frac{1}{2n_{\text{lag}}} \sum_{\tau} \sum_{k \in \{2,4\}} \left[\log m_k^{\text{obs}}(\tau) - \log m_k^{\text{mod}}(\tau)\right]^2$$

Preference evaluated with mean adjusted R^2 for the two moment orders.

5 Conclusion

Across the tested finite, depletable landscapes, intermittent search gives higher mean adjusted R^2 than Lévy walks for second- and fourth-order displacement moments. This fit preference does not uniquely identify the generating dynamics.

Evidence: $\Gamma > 0$ for all 18 reported grid–environment combinations.

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