Emergence, Control and Open-Ended Evolution in Cellular Automata

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The Challenge of Open-Ended Evolution

- Open-ended evolution: A fundamental characteristic of biological evolution
- Continuous generation of novelty and increasing complexity
- No predetermined endpoint
- Challenging to replicate in artificial systems







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- Cellular Automata: A powerful tool for ALife
 - Generate complex behaviors from simple rules
 - Examples: Conway's Game of Life, Langton's self-replicating loops



Flow-Lenia

Flow-Lenia demo video presented at the Virtual Creature Contest during

ALife2024 conference: https://youtu.be/sSrHoe-iPiU



Continuous cellular automaton with mass conservation

- Enables multi-species simulations
- Bridges cellular automata and particle-based systems

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Proposed Approach:

- Define relevant metrics to describe evolutionary dynamics
- Use diversity search (IMGEP) to explore the space of Flow-Lenia's evolutionary trajectories

Key Components of Flow-Lenia



- Activation of a cell interpreted as density of matter
- Compute a potential map from the current state
- Interpret the gradient of the potential map as a flow field
- Move matter along the flow field using reintegration tracking
- Update local parameter according to incoming matter



Parameter Interactions and Mixing Rules in Flow-Lenia



(c) Average mixing



(b) Kinetic-based selection



(d) Negotiation rule

Negotiation Mixing Rule



- Complex interactions between different local parameters
- Potential new behaviors: improved defense against external invasions, matter exchange without loss of identity, specialization for specific local environments
- In practice we observed that the negotiation rule displayed generally more complex patterns and behaviors

From Flow-Lenia to Systematic Exploration

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- Challenge: Efficiently discover conditions for open-ended evolution
- Random sampling inefficient for high-dimensional spaces
- Solution: Intrinsically Motivated Goal Exploration Processes (IMGEP)

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Why IMGEP?

- Maximizes coverage of behavior space (diverse evolutionary dynamics)
- 2 Efficiently explores high-dimensional parameter spaces with non-linear interactions between parameters
- 3 Leverages previous explorations to guide future sampling

Our Approach: Explore diversity of evolutionary dynamics to bootstrap open-ended evolutionary processes in Flow-Lenia

IMGEP: Systematic Exploration of Flow-Lenia



- Intrinsically Motivated Goal Exploration Processes
- Efficient navigation of vast parameter spaces
- Goals defined by evolutionary metrics
- Iterative discovery process

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- Movement via Wasserstein Distance
 - Measures matter redistribution between states
 - Captures dynamic aspects independent of local parameters and update rules

Non-neutral Evolutionary Activity

$$A = \sum_{i} \sum_{t=1}^{i} \Delta_i(t)$$

T

$$\Delta_i(t) = egin{cases} (p_i(t) - p_i(t-1))^2 & ext{if } p_i(t) > p_i(t-1) \ 0 & ext{otherwise} \end{cases}$$

where:

- A: Total evolutionary activity
- $\Delta_i(t)$: Instantaneous activity of component *i* at time *t*
- *p_i(t)*: Proportion of simulated mass attributed to component
 i at time *t*

Comparison of Mixing Rules



IMGEP Results



- Outperformed random exploration
- Discovered diverse dynamics
- Rules with higher evolutionary activity
- Lower entropy of the matter distribution
- New combinations of metrics

IMGEP vs. Random Search

Algorithm	Avg Pairwise Distance	Coverage	std(EA)	std(MP4)	std(H7)	std(H3)
IMGEP	7.88e-01	1387	3.11e+03	7.76e+05	2.46e-01	5.43e-01
Random Search	4.41e-01	678	1.77e+03	6.55e+05	7.65e-02	3.68e-01

- IMGEP consistently outperforms Random Search across all metrics
- Higher coverage and diversity in explored solution space
- Greater standard deviation in key metrics indicates wider range of discovered behaviors

Evolution of Metrics Over Time



Figure: Evolution of exploration metrics for IMGEP (blue) and Random Search (orange) over time.

Interactive Exploration Tool



Figure: http://flowlenia.thomichel.fr

- Visualize and interact with all discovered simulations
- Select specific dynamics based on metric values
- Facilitates in-depth analysis of diverse behaviors

Diverse Dynamics Discovered by IMGEP



Figure: Wide range of patterns and behaviors discovered by IMGEP

Future Directions

- Investigate impact of initial conditions on evolutionary trajectories
- Develop metrics to better capture temporal and spacial dynamics of evolution
- Use IMGEP to automatically explore environmental conditions and their effects on evolutionary outcomes
- Investigate relationship between visual interest and quantitative metrics
- Extend simulations to study longer-term evolutionary dynamics
- Compare IMGEP with other advanced search techniques (e.g., novelty search)

Key References

- Chan, B. W. C. (2018). Lenia-biology of artificial life. arXiv preprint arXiv:1812.05433.
- [2] Plantec, E., et al. (2023). Flow-Lenia: Towards open-ended evolution in cellular automata through mass conservation and parameter localization. Artificial Life Conference Proceedings 35, 131.
- [3] Forestier, S., et al. (2022). Intrinsically motivated goal exploration processes with automatic curriculum learning. Journal of Machine Learning Research, 23(152), 1-41.
- [4] Reinke, C., Etcheverry, M., & Oudeyer, P. Y. (2020). Intrinsically Motivated Discovery of Diverse Patterns in Self-Organizing Systems. arXiv preprint arXiv:1908.06663.
- [5] Hamon, G., et al. (2024). Discovering Sensorimotor Agency in Cellular Automata using Diversity Search. arXiv preprint arXiv:2402.10236.

Conclusion and Q&A

Thank you for your attention

Questions?

Explore Flow-Lenia: http://flowlenia.thomichel.fr