Survey of Latest Developments in Cellular Automata

<u>Lenia:</u>

Lenia is a system of continuous cellular automata. It was derived from Conway's Game of Life by making everything smooth, continuous and generalized. It is a two-dimensional cellular automaton with continuous space-time-state and generalized local rule. It can support a greater diversity of complex autonomous patterns, "life forms", that differ from other cellular automata patterns in being geometric, matemeric, fuzzy, resilient, adaptive, and rule-generic [1].

The colab tutorial showing the progression from Conway's Game of Life to Lenia is available online:
https://colab.research.google.com/github/OpenLenia/Lenia-Tutorial/blob/main/Tutorial_From_Conway_to_Lenia.ipynb#scrollTo=F1NF30u4JTG4

This tutorial begins by implementing the original Game of Life cellular automata. It generalizes this by using convolution and a growth function. This way, the cellular automata uses a convolution with a kernel instead of counting the neighbors. The growth function replaces the conditional update in the original automata. Once the Game of Life has been generalized in this manner, it is ready to be extended to continuous cases. Larger-than-Life extends it to a continuous space. Primordia extends it to continuous states, and Lenia combines these and extends it to continuous states-space-time.

Larger-than-Life enlarges the kernel we created above to a given radius creating a continuous space.

Primordia allows for multiple states. The growth function is scaled up for the states and the neighbor sum and initial conditions both take these states into account. It helps to normalize the various properties, states, kernel, and growth ranges to restrict their values making further generalizations much simpler. This also effectively makes the states continuous.

We can add to this continuous state cellular automata, Primordia, by defining an update frequency that scales the updates making time continuous as well.

Once we have continuous states and time, we can add in the continuous space from Larger-than-Life. This is where Lenia starts to form. Once the kernel is smoothed using a bell-shaped function and the growth function is also smoothed by the same type of function, we finally arrive at Lenia.

Since the creation of Lenia, many extensions have been discovered. For example, for more efficient calculations, the naive convolution calculation can be replaced by fast Fourier transform. Another extension involves extending the kernel into multiple rings instead of just a single ring. An even more ambitious extension was to extend it to multiple kernels and multiple growth functions making the kernels, neighbor sums, and growth values into lists. Another extension was to extend the world into multiple channels, such as RGB.

Extensions aren't the only way that Lenia has been experimented with. Variants of Lenia have also come about. One such variant involves an asymptotic update changing the growth function into a target function which calculates a target state that the cell should approach. In multi-channel Lenia, growth or target function can be used for different channels, creating even more complex, interesting organisms. The last extension mentioned here involves changing the soft clip function to hard clip which creates smoother patterns and can exhibit long-range sensing.

Some initial experimentation with initial patterns and kernels in Lenia has led to the following observations.

Multiple initial patterns have been discovered in the Lenia framework. When these patterns are paired with a specific kernel, they perform interesting, life-like actions. These initial patterns and kernels are very sensitive to one another. If a stable pattern and kernel are found, deviating slightly from the initialization or kernel can cause the cellular automata to exhibit random noise or crash completely to nothing. There seem to be very few of these stable states compared to unstable ones. An interesting direction for future research could be experimenting with the discovery of the stable, versus unstable, conditions of Lenia.

Several kernels have been applied to the Lenia cellular automata. All of the kernels in the demonstration provided at https://chakazul.github.io/Lenia/JavaScript/Lenia.html, involve unimodal, bimodal, trimodal, and tetramodal kernels of circular rings. If one applies a square ring kernel, the resulting cellular automaton behaves significantly differently. This work was unable to discover a stable state for the square ring kernel experimented with, but it is worth noting that the only technique applied was manual perturbation of the initial state. The square kernel, however, also goes against the "smooth" nature of Lenia, so this could also be a contributing factor. An interesting research direction building upon this could be to use various functions to generate differently shaped / oriented kernels to explore further in this regard. Another interesting direction that has been touched on recently is 3-dimensional Lenia with 3-dimensional states, kernels, and growth functions.

Lenia is a recent extension of cellular automata that has an immense amount of potential for experimentation and discovery and has already started to see attention from researchers. There is still much to be discovered in regards to almost every aspect of Lenia's composition and theoretical implications. This work only begins to present the possibilities that Lenia offers.

Simulating morphogenesis with CA

Morphogenesis is the process in which order is developed in a growing organism. This organization begins at the cellular level, in which cells organize themselves and differentiate into tissues, organs, and eventually an entire organism. The mechanisms behind morphogenesis have been investigated since the 1920's, when studies were performed to investigate regions of the embryo responsible for creating body structures. As more discoveries were made, focus shifted to applications such as limb development, limb regeneration, and growth coordination, however many questions still remain today on the mechanisms behind morphogenesis and how they can lead to the formation of an organism [2].

Rasolonjanahary et al. utilized von Neumann cellular automata to study the formation of morphogenic patterns due to short-range interactions. By investigating local interactions in the formation of periodic patterns, the mechanisms behind biological pattern formation can be better understood. The authors utilized one-dimensional cellular automata to discover what rules result in the formation of stationary periodic patterns that: allow for recovery conservation of periodic patterns, allow for local recovery of periodic patterns perturbed by noise, and allow for the formation of two-periodic patterns from random initial conditions. The two-state model utilized in this study is representative of cells either expressing a gene or not expressing a gene. Out of the 256 rules of elementary cellular automata, it was determined that 64 rules allow for existence of two-periodic patterns, 33 allow for recovery of two-periodic patterns, and only 6 allow for the formation of two-periodic patterns from initial conditions. While the growth of tissues, organs, and other biological development take place in three-dimensional space, pattern formation can accurately be represented as a one-dimensional process. The authors state that further study is warranted to model the formation of patterns in a growing medium and to perform a similar analysis on a four-state CA system [3].

Growing Neural Model of Cellular Automata – Differentiable Model of Morphogenesis

Mordvintsev et al. implemented a neural network to develop a cellular automata update rule that grows and regenerates cells based on the image that was provided. Through experimentation *in silico*, morphogenesis and self-repairing aspects of biological systems can be modeled to help provide deeper insights into the mechanisms behind these processes.[4]

Here they modelled the transition function of the CA using a convolutional neural network that updates the cell positions based on 3x3 cell neighborhood states with updates performed synchronously with stochasticity.

Using neural networks and gradient based optimization techniques, they are able to train a network that can find the transition function growing into the target pattern from a seed state. By training from successive states of the CA after n steps, they are able to achieve a stable target post the CA steps used in the training. The NCA is also able to recover once the target is damaged, simulating repair capabilities.

The use of Neural Networks to capture local communication patterns of cell states and gradient optimization techniques to find the weights, provides a powerful tool to generate interesting behavior with Cellular Automata.

Future Work

1) Introduction to Graph Cellular Automata
2) Lenia - theoretical results
3) Neural Cellular Automata behavior with SelfOrganizing CA.

References

[1] Chan, B. W. C. (2018). Lenia-biology of artificial life. *arXiv preprint arXiv:1812.05433*.

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[3] M. Rasolonjanahary and B. Vasiev, “Formation of morphogenetic patterns in cellular automata,” *arXiv:2002.06112 [nlin]*, Jul. 2020, Accessed: Nov. 29, 2021. [Online]. Available:

[4] Mordvintsev el al. https://distill.pub/2020/growing-ca/