Evolution of Self-Replicators within Cellular Automata: 25 Years After Evoloops

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Abstract

The year of 2023 marks the 25th anniversary of the discovery of *evoloops*, which proved that Darwinian evolution of self-replicators by variation and natural selection was possible within deterministic cellular automata. This line of research has since undergone several important developments. Although it experienced a relative dormancy of activities for about a decade, the recent rise of interest in open-ended evolution and the success of continuous cellular automata models have brought researchers' attention back to how to make spatio-temporal patterns self-replicate and evolve within spatially distributed computational media. This presentation provides a brief review of the relevant literature on this topic over the past 25 years and highlights promising future research directions.

June 1st, 2023 marks the 25th anniversary of the discovery of *evoloops* (Sayama 1998, 1999a, 1999b), the first cellular automata-based artificial life that exhibits true Darwinian evolution of self-replicators by spontaneous variation and natural selection. Creating such a demonstrative evolutionary process within artificial media like cellular automata was one of the original goals set by founding pioneers of artificial life (von Neumann 1966; Langton 1984, 1986). However, this line of research remained rather unpopular and unexplored ever since, likely because of the lack of rigorous theories, generalizability of models, and immediate applications to practical problem solving. Nonetheless, several important developments were made since the proposal of evoloops, and more recently, artificial life researchers began to pay attention again to how to make patterns self-replicate and evolve within spatially distributed computational media, potentially leading to open-ended evolution.

The original evoloop model (Sayama 1998, 1999a, 1999b) was a 9-state 2D cellular automata model with von Neumann neighborhoods, derived from Langton's self-reproducing loops (Langton 1984). Its state-transition function was revised so that it would operate more robustly under a greater variety of local situations and that any undefined situation would generate a "dissolving" state that would propagate through contiguous active states and erase them from the space (structural dissolution). Direct interactions (collisions) of evoloops caused irregular situations during their replication process, naturally inducing variations of their genetic codes and thereby achieving spontaneous evolution of self-replicators toward the fittest form (smallest ones in most cases; Figure 1) (Sayama 1998, 1999a). This system was also known to demonstrate substantial fault tolerance and, with slightly revised state transition function, abiogenesis from an initial configuration with no ancestor replicators (Sayama 1999b).

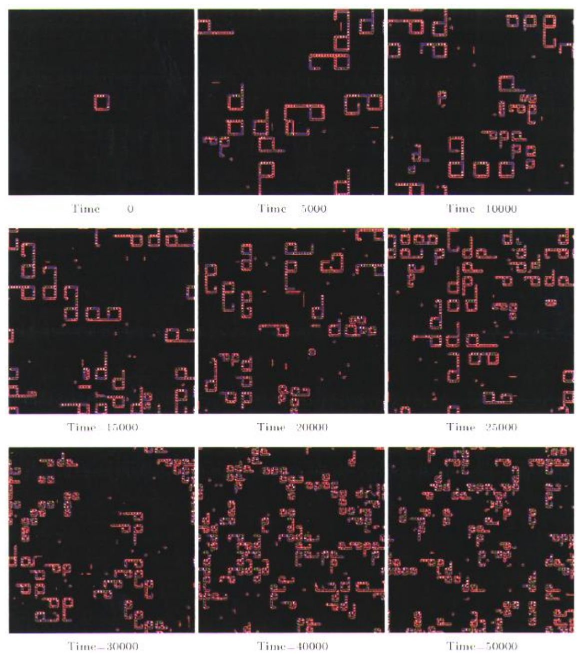

Figure 1: Spontaneous evolution of evoloops (figure from (Sayama 1999a)).

The proposal of evoloops triggered several subsequent studies that implemented important developments. Nehaniv (2002) expanded the model to asynchronously updated cellular automata and showed that evolution can occur even without synchronous updating. Sayama (2004) introduced self-protection behaviors of individuals and showed that it would help promote the diversity of species. Salzberg and Sayama (2004a) conducted detailed genetic sequencing of all the individual self-replicators that appeared in simulations and found that their genotypic/phenotypic diversities were much greater than originally thought and they continued to evolve for a long period of time after the loops' size reached the smallest level. Salzberg et al. (2004) also studied the evolutionary dynamics of evoloops in dynamic, hostile environments. Moreover, Oros and Nehaniv (2007) proposed a revised model in which loops engaged in sexual reproduction by exchanging genetic information when colliding with each other, and they also showed that the capability of sexual reproduction can be evolutionarily maintained (Oros & Nehaniv, 2009). A related approach studied at about the same time was to achieve evolution of self-replicators via the shape-encoding mechanism. It was originally proposed by Morita and Imai (1996) for self-replication of various shapes in reversible cellular automata, but later adopted to promote spontaneous evolution of patterns through their spatial interactions (Sayama 2000; Suzuki & Ikegami 2006). A concise review of research on self-replication and evolution in cellular automata up to mid-2000s can be found in (Salzberg & Sayama 2004b).

Since then, this line of research experienced a relative dormancy of activities for about a decade, probably because the topics of interest in the artificial life community became diversified and shifted more toward evolutionary robotics, neuroevolution, swarm intelligence, agent interactions, and others. During this "lost" decade, there was not much progress made in self-replicating and evolving cellular automata research (but some exceptions exist, e.g., Yinusa & Nehaniv (2011) that studied the inheritability of mutations in von Neumann's self-reproducing automata, and Huang et al. (2013) that proposed self-reproducing loops that adapt their shapes to local spatial constraints).

Interestingly, for the last several years, there has been a resurgence of researchers' interest in spontaneous evolution of self-replicators in cellular automata. This is partly because of the Open-Ended Evolution (OEE) movement (Taylor et al. 2016) that re-ignited the study of evolutionary dynamics within a dynamical system. For example, Adams et al. (2017) systematically investigated how to achieve OEE within elementary cellular automata and showed that dynamic changes in environmental conditions (= transition rules) were most effective for achieving OEE.

Most recently, the success of continuous cellular automata models, such as Lenia (Chan 2019, 2020) and neural cellular automata (Mordvintsev et al. 2020), has attracted many researchers to explore how to create spontaneous evolutionary processes of diverse self-replicating patterns within a continuous cellular automata space. This is a very recent development that has been taking place only within the last year or two. For example, Sinapayen (2023) trained neural cellular automata so that they replicate given organism patterns, and demonstrated that the replicated patterns would deviate from the ancestor pattern over time, suggesting genetic/phenotypic drift through multiple generations. Also, Plantec et al. (2022) and Chan (2023) studied Lenia-based evolutionary systems in which model parameters were associated with each location and diffused over space (with mutations) so that multiple species and their interactions could be simulated simultaneously within a single simulation run (Figure 2). This is similar to the "recipe" propagation approach used in evolutionary Swarm Chemistry models (Sayama 2011) with great potential to generate a broad range of self-replicating spatio-temporal patterns automatically and efficiently.

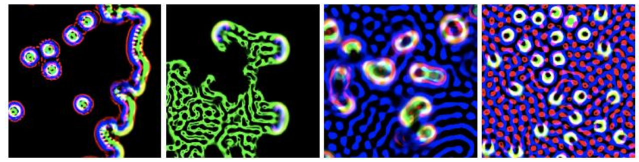

Figure 2: Various patterns evolved within Evolutionary Lenia (images courtesy of Bert Chan; from (Chan 2023)).

These recent developments that utilize continuous cellular automata are very promising and expected to produce further advances in self-replication and evolution research. Meanwhile, many key questions still need to be addressed, and here we discuss only a few.

First, nearly all the above evolutionary systems built within spatially distributed media exhibited the eventual dominance by one or a few most successful species in the long run, and it is still unclear what kind of generalizable principles or mechanisms are available to prevent the evolving ecosystem of self-replicators from falling into such pseudo-equilibrium states. It has been suggested that dynamic environments (Salzberg et al., 2004; Sayama 2011; Adams et al., 2017) are the key to addressing this issue, although they may not work for indefinitely long terms (Sayama 2018).

Second, the recent approach to assign model parameters to local regions/agents deliberately avoids explicit representation of such genetic information in the space, in contrast to real biological systems and earlier self-replication models (von Neumann 1966; Langton 1984; Sayama 1998, 1999a, 1999b) where genetic instructions were explicitly represented in space. It is not well understood how these two approaches differ regarding the open-endedness and creativity of their evolution.

Third, all the models reviewed so far relied on either logically designed mechanisms written in discrete state-transition rules or dynamically generated quasi-stable patterns in continuous space, but neither would capture the *autopoietic* nature of real biological systems. There is another major body of literature on computational autopoietic models (McMullin, 2004; Nehaniv, 2005; Ikegami & Suzuki, 2008; Suzuki & Ikegami, 2009; Sirmai, 2011, 2013), and some of them even demonstrated self-reproduction of autopoietic structures (Sirmai, 2013). However, it remains unclear how one could integrate autopoietic dynamics into existing cellular automata models of evolving self-replicating patterns.

Finally, the relationship between the evolutionary dynamics of those self-replicators and the "intelligence" therein is worth further quantitative investigation. Intelligence is often associated with computational universality and critical behavior, and therefore, it may be characterized by the incompressibility/irreducibility of spatio-temporal dynamics. It would be quite interesting to quantify how much compressibility/reducibility the spatio-temporal dynamics of evolving self-replicators would have, and how it would change over time in the course of their evolution. If one could create evolutionary cellular automata that become increasingly harder to simulate over time, that would indicate the increasing complexity (= computational capability, "intelligence") of evolving entities within spatially distributed media. This would be a direct, concrete, measurable demonstration of the very original motivating vision posed by von Neumann (1966).

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