Characterization of Multispecies Living Ecosystems With Cellular Automata

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Abstract

A multispecies artificial ecosystem is formulated using cellular automata with species interactions and food chain hierarchy. The constructed finite state automaton can simulate the complexity and self-organized characteristics of the evolving multispecies living ecosystems. Simulations show that a small perturbation or extinction event may affect many other species in the ecosystem in an avalanche manner. Both the avalanches and the extinction arising from these changes follow a power law, reflecting that the multispecies living ecosytems have the characteristics of self-organized criticality.

Introduction

The modelling of artificial life is very important to the understanding of the origin of life and its evolution, thus the studies using computer simulations are very important. Since Langton (1986) relaunched the field of artificial life, the possibly universal aspects of living systems have been investigated by exploring artificial chemistries acting on artificial molecules in terms of rule-based cellular automata (CA). Langton (1986) carried out numerous CA simulations with a parameterization scheme allowing the relationship of Wolfram's classes cataloged the rules that generates different classes of dynamics. Since then there have been many extensive studies about artificial life. Artificial life simulations using cellular automata have received much of interests in the community of artificial life and evolutionary computing. Wolfram (1983, 1984, 1994) pioneered the classification and systematic studies of the complexity of cellular automata. Conway's Game of Life has popularized this area of research. However, most of the existing simulations of CA is about the evolutionary and classification of one single species, and this has demonstrated the complexity and richness of simple rule-based systems. Interestingly, multispecies models have begun to attract much attention (Sole and Manrubia, 1996; Amaral and Meyer,1999). In order to study the ecological effect and the interaction among different species, a multispecies system of artificial life should be explored in detail. It can be expected that the behavior and characteristics of multispecies living system could be very different from that of a single species cellular automaton. Several simulation platforms for artificial life have been developed such as `Avida` and `Tierra`. These powerful platforms can simulate an artificial environment on a two-dimensional grid with rule-based interactions. However, the understanding and studies of artificial life is still at a very early stage.

Since the pioneer work by Bak (1995) and Adami (1995) on self-organized criticality, there have been several studies on the criticality in living systems and other physical systems (Adami, 1995; Abramson and Zanette, 1998; Kauffman, 1995; Gil and Sornette, 1995; Sole and Manrubia, 1996). However, Newman et al (1997) argued that it may not be so. Thus, it still remains as an open issue and the studies of self-organized criticality in different systems require more work. In addition, more studies on the complexity of a multispecies artificial ecosystem and how the local rule-based interactions affect the behavior of the development of the ecosytem are highly needed.

The aim of this paper is to present some new results using a multspecies system of artificial life with cellular automata. By numerical experiments, we will find how the interactions among different species affect the evolutionary behavior and self-organization as well as species extinction events. This paper is orgainised as follows. In the next sections, we describe how to construct the cellular automaton for a multispecies living system, we then implement the system and give some simulations. Based on the simulations, the complexity and entropy of the evolving living system are measured, and the self-organized criticality is tested. The possible reason of extinction behavior of the living system is also explored. The implications of the multispecies interactions will be also discussed.

Rule-Based Cellular Automata for Multi-Species Living Systems

Cellular Automaton (CA) is a finite-state machine on a regular lattice. The input to the machine is the states of all cells in its neighborhood, the change of its state is based on the rules or transition functions. The states of all cells in the lattice are updated synchronously in discrete time steps. Each cell evolves according to the same rules which depend only on the state of the cell and a finite number of neighboring cells, and the neighborhood relation is local and uniform. One classic example is Conway's game of life where one takes a neighborhood consisting of the nearest 8 cells to a cell on a 2-D cellular automaton. Its transition function for the local automaton for two states (1 and 0, or alive and not alive) is as follows: If 2 or 3 neighbors of a cell are alive (or 1) and it is alive at present, then it is alive at next state; If 3 neighbors of a cell are alive and it is currently not alive, its next state is alive; the next state is not alive for all the other cases. Even with these simple rules, a universal computational machine can be constructed on an infinite 2-D grid, which is capable of emulating the computing power of any Turing machine or digital computer.

The present model is an extension of the combined version of the Solé-Manrubia model (1996) and Amaral-Meyer food chain model (1999). The next state C_i for a cell i is determined by the transition function in the general form

$$C_i(t+1) = H[\sum_j G_{ij} C_i(t) - \theta], \tag{1}$$

where H is the Heaviside step function, and θ is the threshold. G_{ij} of the influence of cell j on cell i, $G_{ij} > 0$ or < 0 if j is the food or predator for cell i. The summation is over the nearest neighborhood. The multispecies cellular automaton works in the following way:

1. The CA consists of M interacting species, when $M = 1$ it degenerates into the classic Conway's game of life and obeys the same simple rules.

2. Different sepcies interacts with each other in a way of food chain hierarchy. Each species is label as a hierarchy level and for simplicity, we use the level i for species i with species $i-1$ as the pray or food for species i and species $i+1$ as its predator.

3. In the nearest 8 cells of to a cell of species i, if the number of predators is greater than the number of preys, and the cell is currently alive, then its next state is not alive; If the number of the preys is more than the number of predators, then its next state is alive whether its present state is alive or not; If the predators are in the same number as the prey, the present state does not change.

4. If there is no predator or pray in the 8 neighborhood cells, then the transition function is the same as the single species Conway's cellular automaton.

In the numerical simulations, the 2-D lattice is randomly initialized with the highest population of the lowest level of species $i = 1$. Updating is synchronous. For

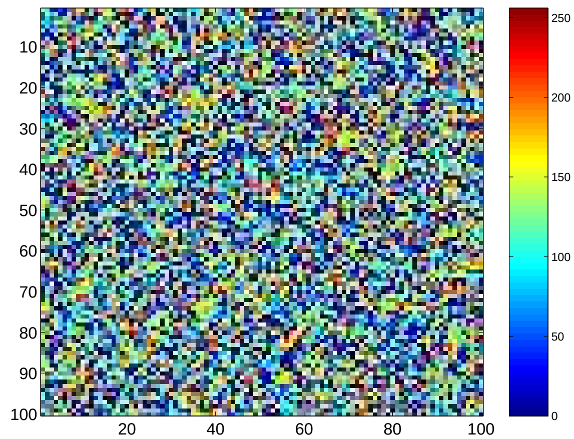

Figure 1: A random configuration of a multispecies cellular automaton with a lattice size of 100×100 and 256 species represented by different colors.

a regular 100×100 lattice with $N = 256$ species initialized this way, we can investigate the complexity, self-organization, species interaction and avalanche events.

To simulate the effect of species interaction and extinction, a small probability of extinction rate is also introduced into some species, the influence of the extinction of one species on the other species in the food chain model can be studied in some detail. In addition, by introducing some extra population in one species, one can control some other species in the food chain model and give important implications on the ecological effect in reality such as the control of growth rates. A number of numerical experiments have also been investigated. Some trend and self-organized criticality is analyzed from the simulated results.

Computer Simulations

By using the cellular automaton described in the above section, we can simulate the behavior of a multspecies living system with multispecies interactions in a food chain hierarchy. In the rest of this paper, we present some results from a huge number of the simulations and parametric studies. A typical initial configuration is shown in Figure 1.

Variation in Complexity and Entropy

For a population size of $N = 100 \times 100$ with $M = 256$, the complexity of the cellular automaton can be measured by its entropy S

$$S = -\sum_i p_i \log p_i, \tag{2}$$

where p_j is the probability of find the species i in the total population (Adami,1998). For a finite population

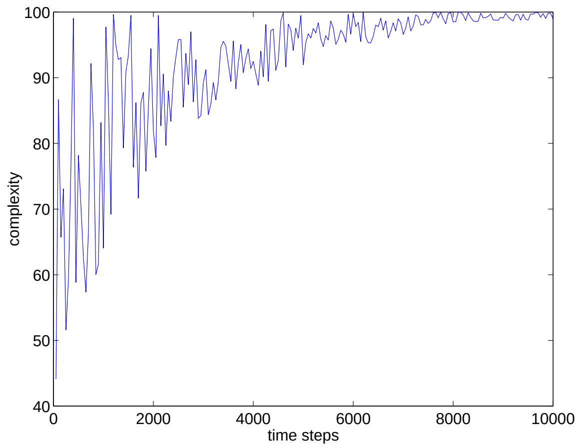

Figure 2: Variations of complexity versus time steps

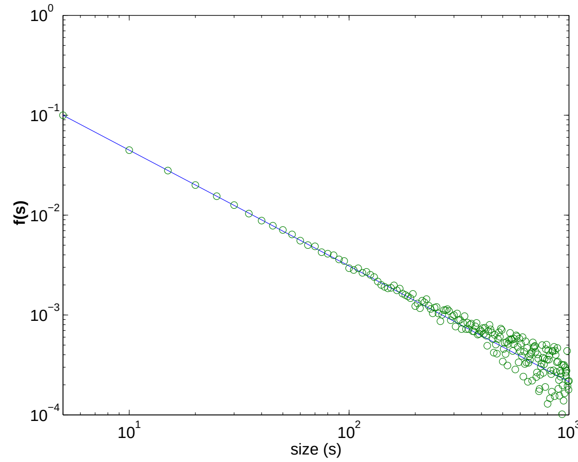

Figure 3: Self-organized criticality in a multispecies living system. The number of avalanches $f(s)$ is a function of avalanche size s. The exponent of the related power-law is $\gamma = 2.26 \pm 0.04$.

size, p_i can be approximated by the fraction of samples n_i or the number of i^{th} species in the N-species,

$$p_i = \frac{n_i}{N}. \tag{3}$$

The variation of complexity of the 256-species cellular automaton is shown in Figure 2.

It is clearly seen that the complexity varies significantly at the early stage of the development process, then it gradually relaxes to the equilibrium at long time, indicating that the living system is in a quasi-steady state among different species. The relaxation time is typically about 10,000 from an initial configuration to a relative stable pattern or a dynamic equilibrium.

Self-Organized Criticality

Based on the pioneering work by Adami (1995) on the self-organized criticality in living systems using the `Tierra` experiments, there is a good reason to believe that self-organized criticality exists in the artificial living system. However, the view of self-organized criticality has been challenged by Newman et al (1997) on the ground that the criticality is usually associated with second-order, not first order, critical phenomena. Gil and Sornette (1996) argued that self-organized criticality can be described in terms of first-order transitions.

In order to test whether the self-organized criticality exists in the multispecies living ecosystem, we introduce a small perturbation to ecosystem and measure the population changes affected by the perturbation or avalanche in population and species, this is because the ecosystem can form between all the competing and yet interconnected species. The change in response to any perturbation will enable this living to relax to a new equilibrium or the self-organized state. By tracing the 15000 avalanches obtained from simulations on 100×100 lattice grid, the results are shown in the log-log plot in Figure 3.

This figure clearly show that the avalanches size distribution follows a power-law with the exponent $\gamma = 2.26 \pm 0.04$. This implies that the multispecies living ecosystem has the characteristics of self-organized criticality. This is consistent with the earlier work by Adami (1995). Our present work implies that the self-organized criticality could be universal in living systems.

Extinction

In the above computer simulations, the changes or redistribution of populations of different species have been studied. There may not necessarily involve the extinction of some species. In some case, for example, when the initial population size for some species is very small and its predators are strong, the whole species could become extinct, and the extinction of one species may influence other species in the food chain. To simulate this effect, we introduce an extinction probability $p_e = 0.01$ for a species at some level, say $i = 16$, in the food chain hierarchy. The extinction obtained from the simulations is shown in Figure 4.

The extinction intensities at different time stages (100 time steps as a stage) follow a power-law with an exponent $\gamma = 2.05 \pm 0.1$, which implies that extinction is a self-organized phenomenon. This is consistent with the fitting data $\gamma = 1.7 \pm 0.3$ from the fossil record (Newman and Eble, 1999), and the extinction is a result of external change and species competition.

Discussion

The multispecies ecosystem of artificial life have been formulated in terms of 2-D cellular automata of the combined Sole-Manrubia type together with the Amaral-Meyer food chain model. By using the proper interac-

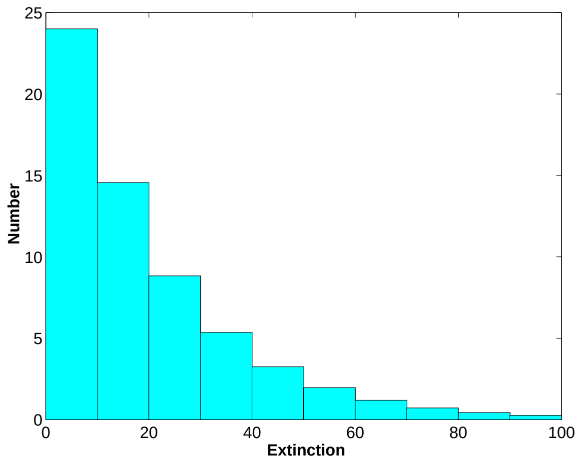

Figure 4: Extinction intensities or number of extinct species at different time stage. The fitting of a power law gives the exponent $\gamma = 2.05 \pm 0.1$.

tions between different species in the food chain hierarchy and the transition function, the finite state automaton can simulate the complexity of the evolving multispecies living ecosystem. Numerical experiments show that the complexity measured by the system entropy fluctuates at early stage of development, then it evolves to the self-organized or dynamic equilibrium sate under certain conditions. By introducing the extra fraction of population or a small perturbation, the species population may be affected at different scales. The avalanches arising from these changes obey a power-law with the exponent $\gamma = 2.26$, reflecting that the multispecies living ecosystem has the characteristics of self-organized criticality. This implies that the self-organized criticality arises naturally in the mulitspecies artificial ecosystem.

One the other hand, in the case of one species in the margin of extinction, it can affect many species in the multispecies living system and can lead some kinds of mass extinction. Simulations also show that the extinction intensities follow a power-law form with the exponent $\gamma = 2.05$, thus indicating the species interaction and competition is the mechanism for the extinction under the action of external changes. Although the present modelling provides a lot of features about the complexity of the artificial living system, much more work is clearly needed to investigate the system behavior such as how different extinction mechanisms and transition rules affect the development of a multispecies living ecosystem.

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