Моделі Штучного Життя в Клітинному Просторі Ресурсів

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Artificial Life Models in Cellular Resource Space

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***Анотація*—Розглядається підхід, заснований на моделюванні складних адаптивних систем, відомий як штучне життя. Такий підхід дозволяє роботу з внутрішньої адаптацією системи, з впливом організму на його навколишнього середовище та інші організми, зі зміною всієї біосфери і в кінцевому підсумку зі своєю власною можливістю існувати, тобто його власна придатність. В області досліджень штучного життя цифрових екосистем, такий підхід дає можливість простежити апостеріорну придатність, який можна розглядати як один з ознак виникнення властивостей системи, таких як чисельність населення, угруповання або стабільності виставленої поведінки. У цій статті розглянуто модель, схожу на класичні моделі штучного життя на просторової решітці і обговорено відносини між агресивною та мирною поведінкою через доступні ресурси в системі. Гетерогенний ландшафт ресурсів і його вплив на поведінку агента вводяться і розглядаються з точки зору стійкості видів. Також досліджувалася стійкість видів.**

***Abstract*—The individual-based approach in the modeling of complex adaptive systems, known as Artificial Life, is considered. Such approach allows dealing with the intrinsic adaptation of a system, with the influence of an organism on its environment and on other organisms, with altering the whole biosphere and eventually with its own possibility to exist, i.e. its own fitness. In the Artificial Life research field of digital ecosystems, such approach provides the ability to trace an a posteriori fitness, which can be treated as one of a system's emergent features like population size, grouping or stability of exhibited behavior. In this article, we explore the model similar to classic Artificial Life models on spatial lattice and discuss relation between combat and peaceful behavior due to available resource in the system. The heterogeneous resource landscape and its impact on agent's behavior is introduced and examined from the point of view of species sustainability. The species sustainability is also investigated.**

Ключові слова—моделі, штучне життя, колективна поведінка, клітинний простір, агресивні стратегії

Keywords—models, artificial life, collective behavior, cellular space, aggressive strategy

I. Introduction

Artificial Life (Alife) is an interdisciplinary research field, which tries to investigate and use the properties of living systems or systems which include a large number of living components (for example, individuals). Alife usually brings together biologists, philosophers, physicists, computer scientists, chemists, mathematicians, artists, engineers, and others. Alife applications are numerous and belong to different research fields such as artificial (digital) ecosystems, artificial society, evolutionary robotics, biology, origin of life (see for example [1], [2], [3], [5], [18], [21], [22], [24]), and many others. Alife systems have been implemented as software and as hardware (see recent reviews [11], [22]). One of the important examples of the software Alife studies builds and explores digital ecosystems that provide novel methods to study evolution. These studies can be useful in answering questions about laws how evolution works and how to manage it. Traditional evolution in real biological systems is extremely slow for study. The computational Alife aims to put the evolution process into action on a computer, so the speed of evolution is only limited by processor performance. Embracing evolution instruments opens opportunities for researching a great variety of problems that are linked with it. Artificial evolving systems are used to build complex systems that expose intellectual behavior and to study the link between intellectuality and complexity [15]. Alife systems are plausible playground to explore the mechanisms of adaptation: general evolving system features such as speciation ([14], [15]), aging ([17]), cooperation ([19]), developmental processes in artificial systems [10], and learning.

Many models are developed for the purpose of studying social, ecological, swarming, artificial life and other topics. Despite the progress of other models, the interconnection between genotype and phenotype dynamic is still quite an unexplored issue; in current study we reveal an example of such unclearness that lurks in dynamic of the system. As one of the goals of the study, we want to concentrate on more detailed research of an agent phenotype sustainability. Further in this work, we discuss the dependency of combat interaction from input resource value and examine the sustainability of phenotypic assembly formation in homogeneous and heterogeneous spaces. These questions fit into the research field of Artificial Life determined by Bedau [5], and belong to a group of research areas that claim to: Determine predictability of evolutionary consequences of manipulating organisms and ecosystems, determine minimal conditions for evolutionary transitions from specific to generic response systems, determine what is inevitable in the open-ended evolution of life.

Alife consolidate different research fields, such as, for example, hardware and software Alife. It could be used to study the evolution of complexity, robotics, and digital organisms. One of the main approaches of constructing simulation models in Alife is multi-agent methodology that is broadly used in the study of complex adaptive systems. Individual-based approach surmounts difficulties of equation-based models by granting additional flexibility for both development and analysis of the model [11]. The popularity of multi-agent approach springs from early researches such as Sugarspace [12], Bugs [20], Echo [14] and Polyworld [23] models. One of the pioneering models of Artificial Life is the model of bugs on spatial lattice that was proposed by Norman H. Packard [20] denotes the importance of shift from extrinsic to intrinsic adaptation approaches in the modeling of evolutionary processes. The author of [20] defines the intrinsic adaptation of a system as a process of changes in interactions of all parts of the system aiming to fit it and permanently changing the environment. As a result of first simulations of his model, H. Packard introduced the notion of an a posteriori fitness function for the intrinsic adaptation evolutionary process and demonstrated with its help the emergence of specific behavior that is inherent for some individuals. This change in the concept of adaptation shifts the focus to the emerging characteristics of the system that can be treated as an aposteriori fitness function. The examples of such values could be population size over time, sustainability of emerging phenotypic assemblies under different factors such as environmental changes or arm races, and other system features. In particular work the size of agents' group with common phenotype (behavior strategy) is treated as the aposteriori fitness function.

Echo model is a Complex Adaptive System that was built with a purpose of extending genetic algorithms approach to ecological setting by adding geography (location), competition for resources and interaction among individuals (coevolution). The Echo model itself is intended to study different patterns of ecosystem behavior, which are in particular how resources flow through different kinds of ecologies takes place and how cooperation among agents can arise through evolution and arms races. The investigations allow identifying parameters or collections of parameters that are critical for emergence of specific behavior, i.e., to perform sensitivity analysis [14]. Simulation results and their analysis allow scientists to build deep intuitions about how different aspects of the digital ecosystem interact one with another, reveal important dependencies, and provide understanding of how evolution interacts with ongoing dynamics of the ecosystem [14].

In the study [14] Terry Jones reveals dynamics of system that is common for ecology systems. The conditions, under which distributions of this kind are seen, include early successional communities, environments perturbed by toxins or pollutants, and in appropriately sized samples [14]. In his study [13] by analyzing count of species in observed data, Preston showed that abundance of species in such areas has lognormal distributions. In his Echo model, he studied agents' species clustering based on genetic distance, stressed species abundance notion and showed that model exposes similar species abundance distribution characteristic to Peterson's lognormal distribution [13].

Continuing working with Echo model family P. Hraber and B. Milne [16] discovered the notion of the emergence of community assemblies. They showed the existence of agent groups that share common behavior that springs in order to response on interaction rules in model architecture. Certain genotype assemblies (complementary genotypes) were born and formed quasi-stable domination that was based on pairwise interaction between agents. In given work we consider digital ecosystem with such emergent feature and show that changing of system property such as space heterogeneity contributes to sustainability of complementary phenotypic assemblies over time.

The further development of digital ecosystem models are models where complex agent's behavior arises from the first principles: it never was predefined by fitness function and emerges through adaptation process. Remarkable examples of such models are Michael Burtsev's [7], [17] model and Robert Grass' [15] model. Further, Michael Burtsev proposed a model that resembles pioneer Artificial Life's Echo [14] and Bugs [20] models: the agents with simple behavior are acting in a simple space. In the study [7] the author develops latter models introducing kinship (by introducing culture affinity) and using the artificial neural network as a basis for agent's actions. In this model no agents have a predefined strategy, instead it emerges as phenotype feature from agent's actions, defined by the neural network. Some of the strategies expose cooperative behavior, where agents adjust their behavior due to genotypic distance between each other. It was shown that in such model the strategies emerge that correspond to those in well-known game theory - dove-hawk-bourgeois, where dove acts like peaceful harvester, hawk demonstrates aggressive behavior attacking agents in neighborhood, and bourgeois that plays as dove when low on resource and displays hawk strategy in possession of it. Also, two new strategies of cooperative attack (when agents attack only non-relative ones) and defense (when agents gather in one location to defend themselves from aggression) emerged [9]. The similar results with different models are achieved by a research with novel artificial life model with predator-prey behavior in [15], where agents are driven by fuzzy cognitive map. Considering results of artificial life modeling it can be concluded that such approach is not being controversial to game theory but on the contrary is an extension that provides new research horizons, such as finding evolutionary stable strategy, designing an open-ended evolution, exploring new sophisticated agent's behavior, and analyzing system regularities, e. g. persistent emergence of the group behavior and arm races. Correlation between population density and frequency of fight action for the case of rich resources in the model is similar to the analogous correlation extracted from the ethnographic database [7]. By studying the model, Burtsev proposed a novel methodology to categorize agents' behavior into strategies and to trace population genotype dynamic [14].

Analysis of mentioned above researches of Alife models show that they open novel regularities and emergent behavior. Following study of the similar models discovers new aspects of agents' behavior dynamic. Evolution processes in the models of digital ecosystems are far from being clear and traceable, the interconnection between emergent features and system parameters are not yet properly established. In this work, we explore the correspondence of the phenotype sustainability to the heterogeneous or homogeneous resource distribution in space and discuss the dependency of aggressive and peaceful behavior on the amount of income resource. In the following part of this article we provide model description and its rules. We discuss the dynamics of aggressive and peaceful behavior in the next section noting some interesting regularities and displaying the dependency between the behavior and resource available in the system. The next section is dedicated to the description of experiments in the space where resource is heterogeneously distributed, that is, predator-prey, and strategy competition cases. Next, we demonstrate how variability of strategies changes on the type of resource space, concluding the article with discussions and future studies possibilities.

II. Model description

Here we describe as the important example the agent-based lattice foraging model with possible predator-prey behavior which is a development of classical artificial life models [12], [14], [23]. This model follows mainly the Burtsev's cellular automata approach [9], because of the similarities in the neural network type, environment rules, and culture affinity between agents. The major differences between his and ours model are agent's perception and agent's world arrangement. In Burtsev's model arbitrary number of agents can occupy single cell unlike ours model, where only one agent can live in the one cell. Perception in Burtsev's model is based on averaging of the parameters – the agent is aware only of mean attributes (culture affinity) of the whole agents' group in his cell. This follows to more generalized interactions. In our model, agent's perception is significantly different: each agent is aware of each neighbor and his culture affinity. Such architecture provides more individualized interactions and perception and is more in line with classical Alife digital ecosystem models [15], [16], and [23].

Each agent is characterized by culture affinity: 3-dimentional vector. Its coordinates can take possible integer values in [-2, 2] interval. Agents are treated as relatives if Euclidean distance between their culture affinity vectors are less than 0.2 threshold. This vector is also inherited by offspring from his parent with some mutations.

An agent occupies one grid cell in cellular space. He is driven by heading vector that defines a cell in front, where interaction may exist. The agent can perceive other agents in von Neuman neighborhood. Each neighbour cell refers to 2 neural network inputs, one corresponds to relative (whose culture vector similar enough in terms of Euclidian distance) and other to corresponds non-relative agent (except only one input for back cell that tracks non-relative agent). Therefore, the agent can differentiate whether a neighbor is relative or non-relative. Agent's accumulates energy. The agent gains resources by consuming resources of other agents.

Patches that grow at each iteration present the resource. The number of patches to grow is defined at startup and is fixed for the experiment. In the case of homogeneous resource distribution, resource appears in any cell with equal probability and the value of this resource is uniformly distributed in [0,500] interval. New resource is appended to the old one remaining in cell. We can track the average resource input count for each iteration (time step) and the average value of resource distributed per cell.

Each simulation run starts with 10 agents placed in the environment and equipped with 2000 points of resource. Agents have artificial neural network that has small predefined weights. They invoke the action eat when resource is in front cell and suppress move action when agent in in front cell (this action ends with except of losing resource). At first iteration, 1000 of resource patches is randomly distributed in environment.

The experiments were performed with various resource income rates (amount of resource patches that appears on each iteration), various parameter values, and heterogeneous resource landscape to display aggressive and peaceful behavior in system. The following set of experiments was performed on heterogeneous resource landscape to demonstrate predator-prey cycle and competition of strategies. Both homogeneous and heterogeneous resource landscape cases (for different resource income rates) were taken for the next set of experiments to display resource landscape influence on the phenotypic i. e. strategy sustainability.

III. Aggressive and peaceful behavior

Current model is a plausible background for studies of aggressive and peaceful behavior as depending on the number of input resources. Also, the model displays different types of interaction between groups of related agents. The simulation results for different resource input rate are presented in this section.

In case of low amount of resources one of the most effective strategies is peaceful strategy. Agents either do not distinguish between relative and non-relative agents and prefer to stay at rest, or run away from the relatives in order to avoid competition for the resources, or escape the strangers feeling threatened, and other variations of these strategies are presented as well.

Number of cooperative strategies for this resource mode slightly surpass number of non-cooperative strategies (those that do not take culture affinity differences into account). Under the cooperative notion, we consider strategies that distinguish relative and non-relative agents using culture affinity and adjust their behavior to benefit from this. For example, when agents leave area filled with relatives, they reduce competition for local resources, or when agents attack only non-relative agents and make no harm to relatives.

Peaceful strategies dominate at this type of resource income. But this long-term pattern of peaceful strategies domination, can be seen rarely for this regime. Such simulation conditions commonly are not able to provide a peaceful strategy that survives after the first manifestations of aggressive behavior. So the peaceful phases change suddenly to much more volatile aggressive strategies.

For smaller amounts of resources, peaceful strategies play an important role. With an increase of volume of resources, almost all strategies show aggression. Peaceful strategies can no longer exist for significant periods of time as in the previous case. Almost all strategies exhibit aggressive behavior and are very volatile. Calculations display population dynamics with permanent aggressive behavior mentioned in the case of a small number of resources.

For a large number of resource inputs, agents have the ability to completely fill the grid space and competition between strategies becomes sluggish. Thus with a large volume of resources all cells are filled with aggressive and peaceful agents and peace strategies are stable and rarely changing each other.

IV. HETEROGENEOUS RESOURCE SPACE

The next step in the study of the behavior of the model was to investigate the strategy dynamics in the case of the heterogeneous resources landscape.

In this paper, among the whole set of computer experiments that were shown, several deserve the most attention. They illustrate the new modes of interaction between agents that adhere to cooperative behavior. Experiments with heterogeneous space show the modes with competition between strategies. In computer experiments most strategies that engaged in competition were mostly cooperative. We assume as antagonistic the peaceful (absence of the "attack" strategies in the vector) and aggressive (if there is at least one action "attack" strategies in the vector) strategies. System dynamic revealed that behavior strategies with similar behavior (peaceful or aggressive) compete with each other as well as strategies with antagonistic behavior (peaceful versus aggressive). It was found the competition between both antagonistic and between similar behavior strategies.

V. SUSTAINABILITY OF THE STRATEGIES

Considering strategies dynamic from the previous chapters, it can be noted that strategies dynamics from previous section are too volatile – lack sustainability. By encouraging agents' phenotypic assemblies, localization in space through heterogeneous resource landscape, we suppress strategies volatility. It can be useful in the search of evolutionarily stable strategy - the strategy that cannot be invaded by any other strategy in arbitrarily small amounts [4].

It should be noted that strategy does not exhibit evolutionary stability as it is familiar for Game Theory models [19]: a strategy that cannot be invaded by any other strategy present in arbitrarily small amounts.

The alternative classification of agent assemblies in research of population divergence [6] claims that agent population assembly belong to the space of stable instability if under the same conditions different experiments can give different population structure and it is not inevitable that this assembly will be presented in population. All (phenotypic) groups of agents in the given model experiments belong to the set of I groups because of great variability and instability of strategies. These populations are called unstable. In contrast, it is defined as "waist" population, the one that constricts to a single assembly [6]. In the model considered in this study, 'waist' behavior can be exposed by cooperative peaceful or cooperative aggressive phenotypic assemblies when the resources income is high. In this case the cooperative behavior that appeared first is fixed further for entire population. However, tracing strategies evolution is a complicated task due to many reasons such as complex model architecture, and computational performance restrictions.

VI. DISCUSSIONS

In this study, we considered phenotypic assemblies (grouping agents by strategies), their shared behavior and its sustainability under different resource environmental conditions: resource income rate and resource landscape distribution. One of the goals of investigations was to increase phenotypic assembly sustainability during time.

The given model architecture is connected mainly to Burtsev's cellular automata approach [9], but bears significant differences which provide more individualized interactions and make the model more familia to classical Alife digital ecosystem models [15], [16], and [23]. We have illustrated how aggressive and peaceful behavior is dependent from the volume of input resources. Such behavior correlates with resulting behavior in model [9]. This allows to speak about continuation of the model development without losing its emergent features. The goal of new experiments was to make strategies less volatile. And the simulation results for heterogeneous cellular space showed decreasing variability of strategies in such case and provided an opportunity to illustrate the emergence and development of strategies competition.

In experiments with heterogeneous space, we have identified modes of competitive agents' interaction with the complementary and similar behavior. So, paradoxically more diversity of conditions follows to the unification of behavior.

Other very interesting conclusion (or confirmation of intuition) is that the aggressive behavior is more inherent to population when the lack of resources is observed. The examples of illustrated strategy competitions state the question about the nature of phenotypic transition between strategies having both complementary (predator-prey) and antagonistic (predator-predator) interactions. It is to be clarified whether the transition occurs though combat or by peaceful genotype transition. The enhancements on model architecture and analysis could shed light on this question. In spite of powerful and demonstrative strategy analysis methodology, the given model demands precise tracking of agent's culture grouping and genotype dynamic. Culture group members can have various phenotypic (strategy) features. The emphasize on combat actions between agents should be done.

Agent's neural architecture is the very important factor for such kind of Artificial Life models. A simple artificial neural network with no hidden layer can achieve the scope of predator-prey behavior considered in this study as it is implemented in the model. More complex behavior such as group hunting and wandering could be simulated using more sophisticated methods of neuroevolution such as, for example, NEAT (neuroevolution of augmented topologies) [10]. Authors of [10] use the NEAT algorithm to investigate the evolution of effective predator group or group of collective foragers. The crucial advantage of NEAT for multiagent modeling is natural origin of agents' grouping by genotype affinity. This could provide useful insights on agent behavior emergence. Alife models could benefit from NEAT usage by inheriting its methodology of tracking genes evolution through historical markings. It is effective and sophisticated resolution of the speciation tracking problem.

As the possible development of given model and of other models of artificial life, we can pose the following problems: overcoming the great computational complexity of the experiments; improving accounting of interaction between the agent and the environment; replacing the discrete space type with continuous; introduction of new types of interaction between agents.

Software enhancement of models with high computation performance would give the possibility to observe long-term trends that provide valuable efforts for understanding of such type models. The application cross-over to high-performance computation environment is the pending task for many Artificial Life models [9], [15].

The important issue is the introduction and usage of novel analysis method for agent-based complex adaptive systems. For example, Burtsev proposed a promising methodology that considers evolving agents' population as a dynamic system in [8]. The open question is the study of the competition of groups and establishing the intensity of the impact of various factors, such as aggression and phenotype transition strategies, on the success in the competition. In this paper we formally speak in digital ecology terms. But it is possible to extend the models to other fields. One of them is investigation of real society by artificial society models. Other recent applications are the searching principles for arranging evolving teams of robots.

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