Aggressive and Peaceful Strategies in Cellular Resource Space

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Abstract: The individual-based approach in the modeling of complex adaptive systems named Artificial Life is considered. Such approach allows to deal with an intrinsic adaptation of the system, with an organism influence on its environment and on other organisms, with altering the whole biosphere and eventually 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 emergent features of the system like population size, grouping or stability of exhibited behavior. In the work, 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. It is introduced heterogeneous resource landscape in its impact on agent's behavior, and examine it on the notion of species sustainability. The species sustainability is investigated.

Key-words: Artificial Life, Agent-Based Modeling, Cooperation, Cellular Space, Evolution Strategies.

1. Introduction

Artificial Life (Alife) is an interdisciplinary research field, which try 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 more. The examples of Alife fields are numerous and includes artificial (digital) ecosystems, artificial society, evolutionary robotics, biology, origin of life – see for examples in [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]). Remark that one of the important examples of the software Alife studies build and explore 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 computation Alife aims to put the evolution process into action on a computer so time for evolution to go on 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 in purpose to study 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 the more detailed research of 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 approach 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 pioneer 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. Packard proposed to change the point of view on fitness in models of biological systems. He claimed that extrinsic approach of adaptation such that is defined by an a priori fitness function that assumes averaging of the environment and individual interactions could inflict limitations on the biosphere. Such limitation takes place, for the organism affects its environment and other organisms, altering the whole biosphere and eventually its own possibility to exist, i. e. its own fitness [20]. 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 a posteriori 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 a posteriori 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 patterns of behavior that are how resources flow through different kinds of ecologies take place, how cooperation among agents can arise through evolution and arms races. Echo corresponds to a set of Echo models, where the system of agents evolve empowered with combat, trade, move and mate abilities that are conditioned by their genotype and phenotype traits. Echo model consists of agents that are located in two-dimensional grid of sites, and migration is supported. Many agents can occupy one site and there is a notion of neighborhood. The different kinds of resource randomly distributed between all cells. Agents use resource to pay metabolic tax and to perform chasing, combat and mating actions. Reproduction can be sexual (crossover) and asexual (replication with mutation). 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 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. A commonly observed phenomenon is that vast majority of species count relatively a few agents. 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 have 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].

In continuation to work 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. By saying phenotypic assembly we consider group of agents that share similar behavior. It should be noted that such assemblies are less complex than community assemblies presented in Hraber and Milne study because agents action portfolio in that model is wider: its agents can trade and mate in addition. While in particular model phenotypic assembly by definition not necessarily support internal group interactions.

The further development of digital ecosystem models is the 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. One of the main achievements of their research is that agent speciation i. e. phenotypic grouping and distinction emerges without predefined fitness function. Agents occupy niches that expose predator, prey or even more sophisticated behavior without extrinsic predisposition but as the result of the evolutional adaptation process.

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 agent had a predefined strategy, instead it emerge as phenotype feature from agent's actions, defined by the neural network. By doing this, the authors of [7] achieved a great variety of strategies that can take into account kinship of the object they interact with and are constructed from elementary actions as a result of evolution processes. Some of the strategies expose cooperative behavior, where agents adjusted their behavior due to genotypic distance between each other. It was shown that in such model emerge strategies 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 agent attack only non-relative ones) and defense (when agents gather in one location to defense themselves from aggression) were emerged [9]. The similar results with different model achieves research with novel artificial life model with predator-prey behavior in study [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 behavior, and analyzing system regularities, e. g. persistent emergence of group behavior and arm races. The simulation of the model implied correspondence to the evolution of territoriality in animals that is a partial feature of the general process of species and communitis formation. Michael Burtsev's model captured a general for primitive societies trend of increasing of the aggression level with rising resource supply [7]. 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. Proceedings 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 space type and discuss the dependency of aggressive and peaceful behavior from the amount on income resource. In the following part of this article we provide model description and its rules. We discuss the dynamic on aggressive and peaceful behavior in the next section denoting some interesting regularities and displaying the dependency between this behavior and resource available in the system. The next section is dedicated to the description of experiments in the heterogeneous resource space that attracted most attention, 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.

2. MODEL DESCRIPTION

Here below we describe as the important example an 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 to 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 these two models are agent's perception and agent's world arrangement. In Burtsev's model arbitrary number of agents can occupy single cell unlike in 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.

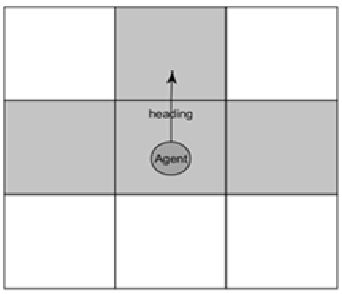

Fig. 1. Agent in the cellular environment and his perception. Agent is aware of resource objects in highlighted cells. The grid size is 25x25 cells.

Agent occupies one grid cell in cellular space (Figure 1). He is driven by heading vector that defines a cell in front, where interaction may exist. Agent can perceive other agents in von Neuman neighborhood. For each neighbor cell is provided with 2 neural network inputs (see Table 1), each of that corresponds to relative (whose culture vector similar enough in terms of Euclidian distance) or non-relative agent (except only one input for back cell that tracks non-relative agent). Therefore, the agent can differ whether neighbor is relative or non-relative. r in Table 1 is the value of resources collected by the agent and rMax is the maximum energy that can be carried. The agent gains resources by consuming resources or 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 all experiment. For the case of homogeneous resources 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 (timer step) and the average value of resource distributed per cell.

The artificial neural network with no hidden layer determines agent's behavior in experiments described below. After birth each agent's offspring inherits the matrix of neural network weights perturbed by some mutations. This matrix is treated as agent's genotype that bears full control of agent's behavior. Here we pose description of neural network inputs and values that they take regarding individual agent's perception and his placement in the environment:

Table 1. Input signals for agent and values that they take. s is the input vector for the agent's neural network. If the statement from the first column is true i.e. object is present in the particular cell, then appropriate coordinate of input vector s is evaluated with the value from the second column.

Input signal	Value
s_0 – bias	rMax (5000)
s_1 – resource in current cell	energy of resource placed in agent's cell
s_2 – resource in front	energy of resource placed in front cell
s_3 – resource in right cell	energy of resource placed in right cell
s_4 – resource in left cell	energy of resource placed in left cell
s_5 – non-relative agent in front	rMax, if there is non-relative agent placed in front
s_6 – non-relative agent right	rMax, it there is non-relative agent placed by right hand
s_7 – non-relative agent left	rMax, it there is non-relative agent placed by left hand
s_8 – current resource value (r)	current resource value (r)
s_9 – (rMax - r)	(rMax - r)
s_{10}– non-relative agent back	rMax, if there is an non-relative agent placed from the back
s_{11}– relative in front	rMax, if in front cell placed relative agent
s_{12} – relative right	rMax, if relative agent is placed by the right hand
s_{13} – relative left	rMax, if relative agent is placed by the left hand

Table 2. Actions and theirs fee or income values. If the output neuron reaches maximum excitation, the corresponding action is selected. The changes of agent's energy level (Δr) are defined by fee\income vector k.

Action	Δr – changes of energy	Value of fee\income (k_i)
f_1 – REST	$\Delta r = -k_1$	5
f_2 – TURN_LEFT	$\Delta r = -k_2$	10
f_3 – TURN_RIGHT	$\Delta r = -k_3$	10
f_4 – EAT	$\Delta r = k_4$	500
f_5 – MOVE_FORWARD	$\Delta r = -k_5$	20
f_6 – DIVIDE	$\Delta r = -k_6$	(20 + r/2), in case of success (r – internal agent's energy); 20, in case of failure
f_7 – ATTACK	$\Delta r = -k_7$	30 and energy that belongs to victim, in case of success; 30, in case of failure
f_8 – ESCAPE	$\Delta r = -k_8$	25

In reply to the input signals agent performs the following actions: 'rest', 'turn', 'move', 'attack', 'escape', 'divide', he pays a fee for each of this actions (see Table 2). Maximum energy value that agent can accumulate is rMax and equals to 5000. Probability to succeed in attack is equals to the ratio of victim's and attacker's accumulated energy. If agent is attacked he asks his neighbor relative agents from Moors neighborhood to help, he can add their energy, multiplied by a coefficient 0.1, to his own energy when defense probability is being counted.

"Divide" action results with producing of an offspring to the environment. The offspring gains half of the parent's energy and genotypic features: artificial neural network and culture vector. This traits are perturbed by mutations with probability rate 0.05 for each coordinate and value taken from uniform distribution in the interval [-30, 30] for the neural matrix and uniform distribution in the interval [-1, 1] for the culture vector. The offspring is placed in a random cell in Moors neighborhood. If all cells are already occupied then the offspring is not created, despite this agent still pays the fee for the action, but not losses half of his energy to the offspring.

Agent's actions are classified into 4 categories: 'wander' – 'rest', 'turn', 'move', 'eat' actions; 'escape' – 'escape' action; 'attack' – 'attack' action, and 'divide' – 'divide' action. Then we consider the strategy vector that encodes most probable agent action in response on specific situations. Each coordinate of strategy vector takes values from classified categories and corresponds to some situation. The vector of agent strategies is generated using the methodology firstly presented in [10]: to show agent's phenotype behavior, each agent was placed in hypothetical situation as if he interacts with other agent under various conditions, i. e. agent's internal energy indicator and agent's relative affinity. After birth, each agent is examined with 6 situations, their enumeration can be seen in Table 3. This process does not affect the simulation itself and is done to display his phenotypic behavior. Particular environmental vector, that is neural network input, corresponds for each situation (see Table 1). For example, to emulate the situation when agent is low on resource and has a relative in front, the vector is evaluated with '0' for all coordinates except rMax for s0 (standard bias), 0,98*rMax for s9 (internal resource input), and rMax for s11 (relative in front input). Thus, the agent is being successively stressed with six input test vectors and then the strategy vector is generated according to his reactions (Table 3). The motivation behind resource division corresponds to the fact that actions seem to have different efficiency, regarding the rate of internal agent's resource. Trivial example is that producing the offspring is rational action for average and maximum internal resource stock, but often is a suicide for low resource reserve. Each situation is encoded in the corresponding rank of strategy vector. For example, if the agent chooses the action "rest" when he is low on resource and a relative is behind, then the first coordinate of strategy vector will be evaluated with '0'. Strategy for vector '020202' is the so-called crow strategy due to [9] (named corresponding to typical crow behavior of mobbing, so that crow would not harm other crow but intend to attack other members of other species). Regardless of internal agent energy level, he will attack any stranger in his area and make no harm to relatives. By referring to the notion of a posteriori fitness function the size of the agents' group with common phenotype (behavior strategy) is treated as an a posteriori fitness function. Here we do not consider other a posteriori fitness functions than agent count, because agent count was explored from the strategy group formation point of view.

Table 3. Each bottom row value corresponds to the coordinate of the vector of agent's strategies a. a_i can take values from the set of actions {0: 'wander'; 1: 'escape'; 2: 'attack'; 3: 'divide'}, i = 1,2,3,4. – in dependence of upper rows conditions:

Low resource, r = 0,02*rMax		Half of resource, r = 0,5*rMax		Many resources, r = 0,98*rMax	
relative in front	non-relative in front	relative in front	non-relative in front	relative in front	non-relative in front
a_i	a_i	a_i	a_i	a_i	a_i

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 reinforce by the action eat when resource is in front cell and reinforce by 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 described in the next section were performed with various resource income rates (amount of resource patches that appears on each iteration) parameter values and heterogeneous resource landscape to display aggressive and peaceful behavior in system. The following set of experiments were 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.

3. AGGRESSIVE AND PEACEFUL BEHAVIOR

Current model is a plausible background for studies aggressive and peaceful behavior in dependence 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 represented in this section.

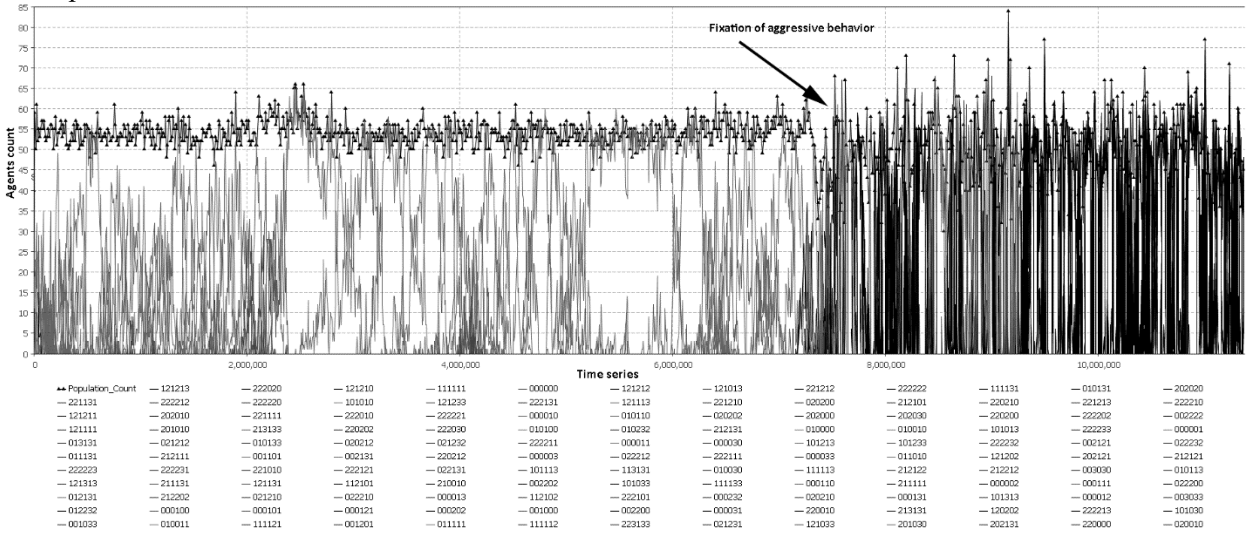

Fig. 2. The graph of agent strategies time dependence in simulation with resource inputs 1,000 units. The x-axis corresponds to time and y-axis is the number of agents with given strategies. Curve marked with triangles correspond to the whole population count. Other curves display the number of agents that expose specific strategy. The legend displays the big number of strategies.

The graph (Fig. 2) shows strategies curves. Each curve displays agents that in some time step share this strategy. If agents choose action to attack, the color range of their strategies shifted to black, otherwise representation shifts to gray.

The run of Figure 2 corresponds to the low amount of input resource – 1000 units. We see the dominance of peaceful strategies, aimed mainly for a search and acquisition of the resource, during the significant amount of time. Remark, that the behavior of the population over time is divided into two conventional stages: peaceful phase (first 7.4 million iterations), and aggressive (after 7.4 million iteration).

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 (for example, the strategy 000000), either run away from the relatives in order to avoid competition for the resources (e. g. strategy 000010), either escape the strangers feeling threatened, and other variations of these strategies.

Number of cooperative strategies for this resource mode slightly surpass number of non-cooperative strategies, those who do not take culture affinity differences into account. Under the cooperative notion should be considered strategies that allows to distinguish relative and non-relative agent using culture affinity and adjust agent 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 ignore relatives.

Peaceful strategies domination occurs at this type of resource income. But this long-term pattern of peaceful strategies domination, as in Figure 2, is rather the exception to as the regime. Such simulation conditions are commonly 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 playing an important role. With an increasing of volume of resources, almost all strategies show aggression. Peaceful strategies can no longer exist for significant periods of time as in the previous cases. 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. It should be noted that the vast majority of strategies considers the relativeness factor for at least one resource value condition in strategy vector (e. g. 022222 strategy agent would not attack relative agent if he himself has low internal resource value and will attack any agent when his resource value increase).

Increased value of environment population capacity as in the time interval of 600 thousand - 800 thousand iterations (Figure 3) usually had been caused by domination of fully cooperative strategies. These strategies distinguish relatives in all cases of the resource value in the strategy vector: 020202 (a strategy known as "crow" in [8]), 020213 ("escape" from relatives to reduce competition for resources), 020203 (action "divide" to secure the neighborhood).

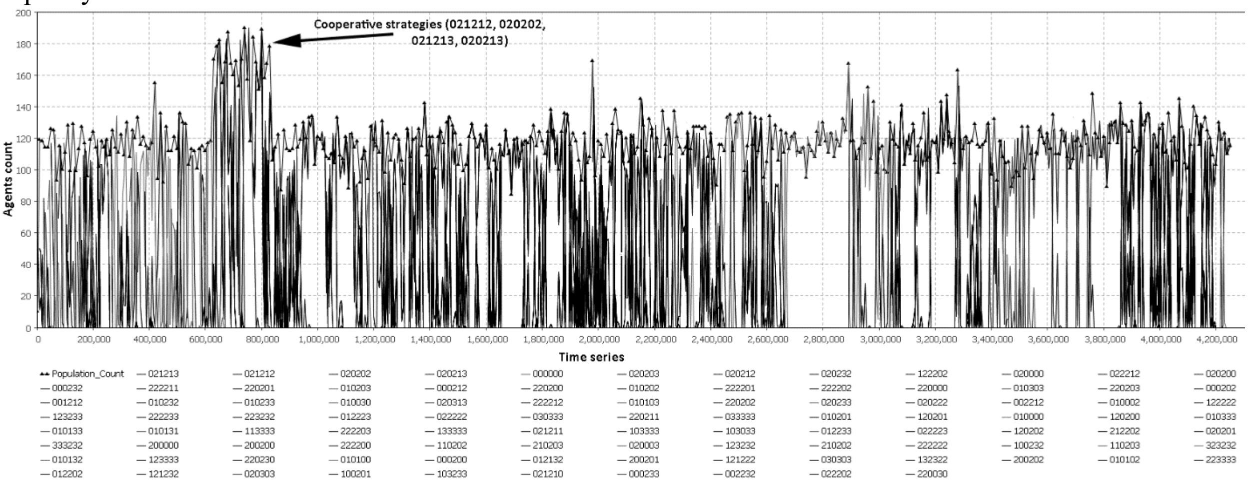

Fig. 3. Strategy for a population in case of middle value number of resources.

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 (Fig. 4).

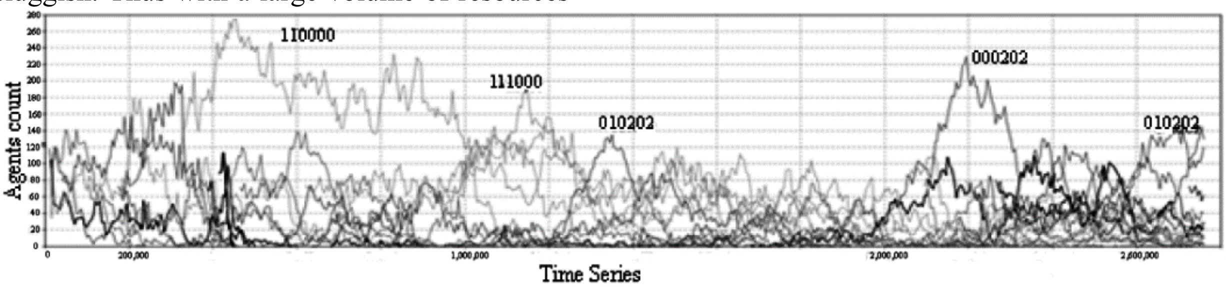

Fig. 4. Agents' strategies for a large number of the resource.

Consider now the generalized dependency of aggressive and peaceful behavior on income resources rate. It is depicted in Figure 5. Frequency of strategies corresponds to y-axis and displays the average rate of agents that expose strategies of peaceful or aggressive type for one simulation run. The strategy is treated as aggressive if it has at least one 'attack' action in its encoding. On the other hand peaceful strategy displays no 'attack' actions. Three different behaviors can be noted at the plot. First behavior corresponds to income resource rate 1000 and remarkable by the relative low share of aggressive actions. This can take place due to low resource that can be gained by praying behavior. Second behavior corresponds to income rate of resources above 1250 and below 3000: the aggression is predominant in the share of all actions. The decrease of aggressive behavior on third interval above 3000 is caused by high resource income rate that is sufficient for one agent to survive in one cell (the mean resource per agent 3500/625=5.6 that is bigger than the fee for 'rest' action, see table 2). The aggressive competition for the resource is suppressed under such conditions. It should be noted that in spite of some differences the dynamic of aggressive behavior is similar for Burtsev's model.

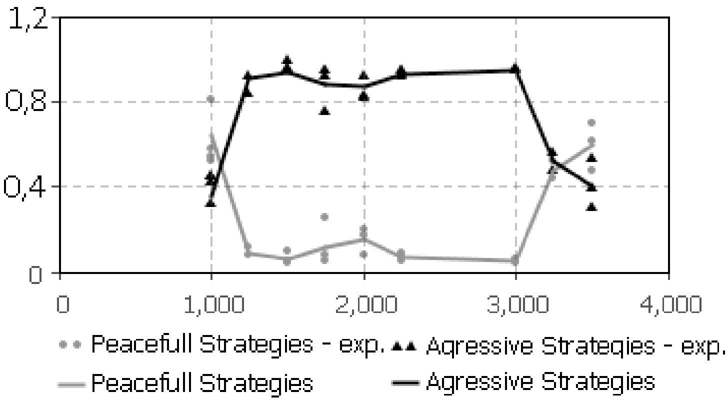

Fig. 5. The dependency of peaceful and aggressive behavior from input resources. The x-axis displays income resource count and y-axis corresponds to the frequency of strategies presented in population. Triangles and circles show experimental values and continuous curves display smoothing of experimental data.

4. 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. An example of environment landscape map is presented in Figure 6. One can see that the resource availability landscape resembles a physical map: lowlands portrayed with lighter color range (gray) and top – darker (black). The map had been generated by uniform distribution of 20 smoothed peaks, so that the mean value for altitude for all cells is 0.4. In the lowlands, the probability for resource to appear is higher than on the high ground. Firstly, random cell is chosed, and the probability for resource to grow in this cell is inversely proportional to its altitude value. (If resource is failed to appear the next try ettempt with another cell is performed). Though the amount of income resource is not changed, its distribution is changed.

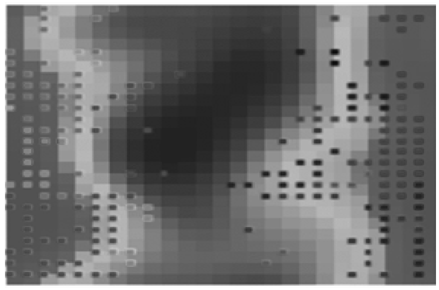

Fig. 6. Map of inhomogeneous medium and agents are on it.

In this paper, among the whole set of computer experiments were shown few that 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. These regimes have been already presented in the case of discrete homogeneous space (which could be easy visible in case of a large number of resources). But due to the high variability for small and medium resource values and by computational difficulties such resource case could not be adequately represented in graphs. In the case of inhomogeneous resource space, agents' phenotypic assemblies were separated from one another by high grounds, and their interaction was limited. This resulted in reducing the variability of strategies and modes in long-term strategy competition.

In computer experiments most strategies 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) strategy. It was found the competition between both antagonistic and between similar behavior strategies.

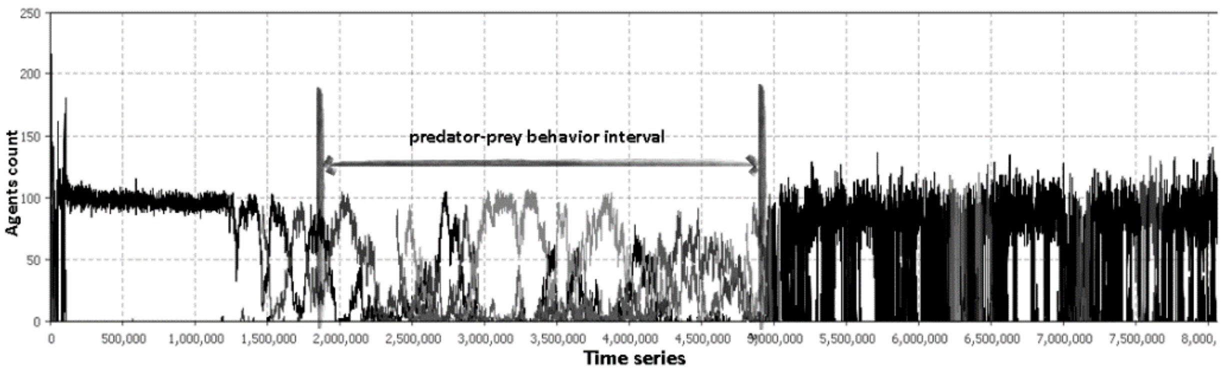

Fig. 7. Strategies chart for simulation in heterogeneous space with competition of strategies.

Figure 7 shows the behavior of the population for the value of input resource 2000 units per time step (clock). The behavior of the population is conventionally divided into two stages: a steady, if only dominated by a few strategies and period with a high value of vicissitudes and aggression for strategies. We show in Figure 8 more details of in the first phase. It displays competitive interaction strategies that alter one another. Consider a closer interval 1.8 - 5 million.

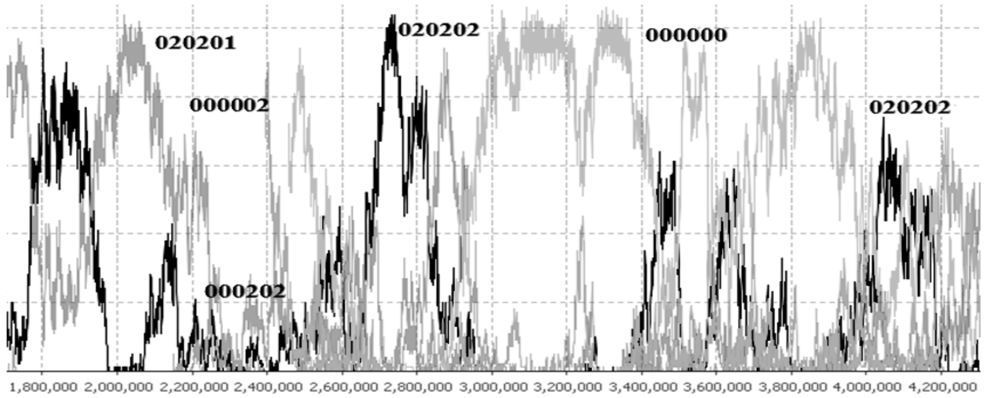

Fig. 8. Details of behavior in interval 1.8 - 5 million iterations from Figure 8. The x-axis corresponds to time steps and y-axis c to the number of agents with different strategies. Peaceful strategies are displayed by grey and aggressive by black.

In Figure 8 we can see the peaks of peaceful population strategy (000000) peaks of population change agents who use aggression against non-relative agents (those agents that have different culture affinity vector) and have the neutral attitude to the related agents (020202, 020200). This behavior resembles the model of predator-prey in population dynamics.

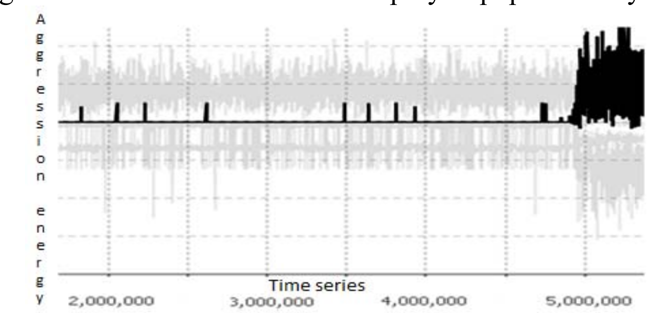

Fig. 9. The x-axis corresponds to iterations and y-axis is energy gain. The black curve displays all energy that agents obtained by performing ‘attack’ action in the case of Figure 8.

If we consider the outbreak of successful aggressive behavior (Figure 9), they occur at points around the largest drop in peaceful strategies: 2500-2600, 3500-3900. However, the pattern of murders reveals that a significant role during the transition of the dominance of one strategy over the other played the genetic switch, as also was mentioned by Epstein J. M. and Axtel R. in Sugarspace model [12]. Also, the similar complementary behavior of phenotypic assemblies appeared in research with Echo model [14]. Thus, the aim of further studies may be setting the real impact of each of these factors (genotypic switch or combat) on forming such behavior.

We had considered also the case of partial competitive strategies, the interaction between the strategies, which have similar behavior. One of the result of computer experiment is displayed below (Fig. 10).

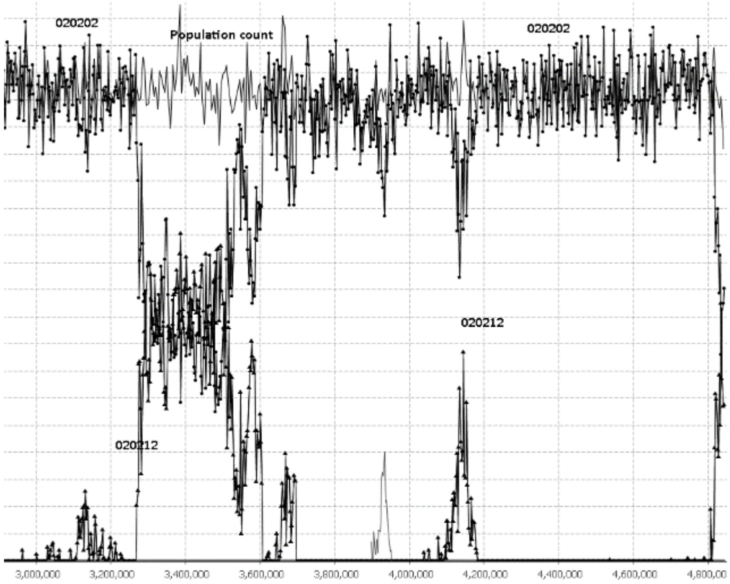

Fig. 10. The interaction between 020202 and 020212 strategies for modeling in heterogeneous space with the number of inputs resource 2334 units.

In this simulation (Figure 10) it can be seen as different locations of related agents (carriers of '020202' and '020212' strategies) on both sides of the landscape compete with each other. In this case, the competitors the 'ravens' ('020202' strategy) could just make another similar strategy that follows the same behavior but with the amendment "the best defense is a good offense". Consider their vector of strategy '020212': value '1' in 5th place in vector means that agents are running away from relatives when their resource is maxed – after accumulating a large number of resources with this strategy agents are moving towards the local formation of non-relatives, which can cause combat. These strategies have more antagonistic than complementary interaction. The main question that arises considering such cases of phenotypic transition is whether they occurs though combat or by peaceful genotype transition.

5. SUSTAINABILITY OF THE STRATEGIES

Considering strategies dynamic from the previous chapters It can be noted that strategies dynamics from previous section are too volatile – luck 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 presented in arbitrarily small amounts [4]. Let us consider a characteristic of the strategies variability that is the frequency of existence of strategies over time. In the previous sections, we looked at the frequency charts of peaceful and aggressive strategies. Obviously, the larger frequency value corresponds to the greater time when strategy is presented in population over time. Usually we had calculated the mean strategy frequency value. Strategy correlates with the phenotype of the species, for it reflects genetically encoded behavior. Such feature could be treated as abundance of species characteristic, because the decreasing of frequency follows to the grows of the rate of species abundance.

Let w_i be the relative frequency of the i-th strategy throughout the experiment: the ratio of the number of time steps when the strategy is presented in population to the total number of time steps. Let us consider the average of the duration of the strategies in the experiment:

$$K = \frac{1}{n}\sum_{k=0}^{n} w_i \qquad (1)$$

Here in the Table 4 we represent the mean strategies frequencies in computer experiments with different values of the resource inputs:

Table 4. Values of average strategy frequencies (K) for different values of resource inputs and types of terrain. The table presents the average values for 4-5 experiments lasting 2-3 million cycles.

Terrain	Small value of input resource (1000-1500)	Average value of input resource (1750-2450)	Large value of input resource (3000-3500)
Homogeneous	0.0061	0.023	0.3
Heterogeneous	0.0074	0.08	0.38

It can be seen from Table 4 that strategies volatility decreased with increasing resource input. Frequency values for heterogeneous landscape are greater than for homogeneous in all cases and much greater for average value resource input. Such results align to the knowledge that environmental variation play an integral role in limiting species' abundance [16].
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 this assembly will be presented in population. All (phenotypic) groups of agents in the given model experiments belong to the space of stable instability because of great variability and instability of strategies. These populations are called unstable. In contrast, it is defined "waist" population, the one that constricts to a single assembly [6]. In model considered in this study 'waist' behavior can be exposed by cooperative peaceful or cooperative aggressive phenotypic assemblies in a large number of resources. In this case the cooperative behavior that appeared first is fixed further for entire population. However, tracing strategies evolution is a complicated task due many reasons such as complex model architecture, and computational performance restrictions.

6. 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 assemblis 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 closer 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 with 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 intrinsic for the lack of resources. The illustrated strategy competitions cases state the question about the nature of phenotypic transition between strategies having both complementary (predator-prey) and antagonistic (predator-predator) interactions. It is needed to clarify 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 agents 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 the work [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 posed 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 on continuous; introduction the new types of interaction between agents and building new computer tools for analysis of populations.

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. Remark that application cross-over to high-performance computation environment is pending task for many Artificial Life models [9], [15].

The important issue is 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. And some final remark. Here at given 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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