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GENOTYPE DYNAMIC FOR AGENT NEUROEVOLUTION IN ARTIFICIAL LIFE MODEL

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Abstract. Cooperation behavior is one of the most used and spread Multi-agent system feature. In some cases emergence of this behaviour can be characterized by division of population on co-evolving subpopulations [1], [2]. Group interaction can take not only antagonistic conflict form but also genetic drift that results with strategies competition and assimilation [3]. In this work we demonstrate different relation between agent grouping and they behavior strategies. We use approach proposed in work [2] methodology of agent genotype dynamic tracking, due to this approach the evolving population can be presented in genotype space as a cloud of points where each point corresponds to one individual. In current work consider the movement of population centroid – the center of the genotype cloud. Analysis of such trajectories can shad the light on the regimes of population existence and genesis.

Key words: artificial life, multiagent systems, neuroevolution

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 [4, 11], and many others. Alife systems are implemented as software and as hardware (see for recent review [10], [12]). 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 operate it. Traditional evolution in real biological systems is extremely slow to 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 study the link between intellectuality and complexity [13]. Alife systems are plau-

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sible playground to explore the mechanisms of adaptation: general evolving system features such as speciation ([2], [13]), aging ([14]), cooperation ([15]), developmental processes in artificial systems [16], 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. By one of the goals of the study, we want to concentrate on the more detailed research of agent phenotype sustainability and what it depends of. 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 [11], 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 [12]. The popularity of multi-agent approach springs from early researches such as Sugarspace [2], Bugs [18], Echo [19] and Polyworld [17] models. One of pioneer models of Artificial Life is the model of bugs on spatial lattice that was proposed by Norman H. Packard [18] 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 [18]. The author 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 model itself is intended to study patterns of behavior that are how resources flow through different kinds of ecologies, how cooperation among agents can arise through evolution and arms races. Echo corresponds to a set of Echo models, in the system 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 each agent is located at a site, 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 trace, combat and mating actions. Reproduction can be sexual (crossover) and asexual (replication with mutation). The system study allows identifying parameters or collections of parameters that are critical for emergence of specific behavior, i.e., to perform sensitivity analysis [19]. 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 [19].

In continuation to work with Echo model family Hraber and Milne discovered the notion of the emergence of community assemblies, they showed the existence of agent groups that share common behaviour that springs in order to response on interaction rules in model architecture [20]. Certain genotype assemblies (complementary genotypes) were born and formed quasi-stable domination that was based on pairwise interaction between agents. In particular 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 behaviour. 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 continuation of digital ecosystem models is the models where complex agent’s behaviour arises from the first principles: where it never was predefined by fitness function and emerges through adaptation process. Remarkable examples of such models are Michael Burtsev’s [2], [21] model and Robert Grass’ [13] 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 behaviour without extrinsic predisposition but as the result of the evolutional adaptation process.

Michael Burtsev proposed a model that resembles pioneer Artificial Life’s Echo [19] and Bugs [18] models: the agents with simple behaviour are acting in a simple space. In the study [2] 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 was given a predefined strategy, instead it emerge as phenotype feature from agent’s actions, defined by the neural network. By doing this, the author 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 behaviour, where agents adjusted their behaviour 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 behaviour 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 [20]. The similar results with different model achieves research with novel artificial life model with predator-prey behavior in study [13], 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. By studying the model, Burtsev proposed a novel methodology to categorize agents' behaviour into strategies and to trace population genotype dynamic [2]. Author proposes alternative view on evolving systems that is inspired by dynamical systems theory. He points that the main notion in this theory is the trajectory and provides mechanisms of tracing the Artificial Life model development as if it moves along its own trajectory. An evolving population can be presented in genotype space as a cloud of points where each point corresponds to one individual. It is proposed to consider the movement of population centroid — the center of the cloud. Analysis of such trajectories shad the light on the regimes of population existence and genesis.

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 can be studied. 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 study the dynamic of agent's population genotype and phenotype using the novel methodologies from Burtsev's work [2]. The aim of the work is to illustrate phenotype and genotype dynamic in continuous space artificial ecosystem model. We open the questions of genotype and phenotype transition and the importance of understanding and tracking the nature of such transitions.

MODEL DESCRIPTION

Agent. Common predator-prey model with continuous space was developed in the work. Agent percepts certain environmental variables such as:

- resource allocated nearby;
- current energy value that belongs to agent itself (r);
- difference between maximum reachable (rMax = 500) and current energy values (*r*);
- the most weaker and the most stronger nearby agent (affected by affinity mark: if agent is relative than input is multiplied with (-1));
- In reply to the input signals agent performs the following actions;
- 'rest': stay on the current position paying the smallest energy price;
- 'eat': start consumption of vegetation. Agent can consume defined vegetation value by one time;

- ‘move’: move towards current heading, if agent sees the vegetation he can change heading in order to reach it. Agent pays specified energy cost for movement;
- ‘attack’: jump to victim agent nearby (hunter pays additional penalty for jump action) and attack him. Attacker pays fee to initiate aggression, if he is successful he gains all victim’s energy (energy consumption is limited by maximum reachable energy threshold) and victim dies;
- ‘divide’: agent creates sibling nearby and gives to him a half of own energy. Sibling receives parent’s genotype with mutations;
- ‘escape’: if one agent wants to escape from another agent, he starts movement in opposite way from target agent with two times higher speed. Actions and theirs fee are listed in Table I.

Table 1. Agent’s fee for actions

Action	**Payment type**	**Value**
Rest	Once per action	15
Move	By overcame path (velocity*step)	25
Move forward		
Divide	Once per action	20 + $r/2$
Attack	Twice by overcame path (2*velocity*step)	50
Escape		

Agent’s behavior is determined by artificial neuronal network with one layer. Each agent’s sibling inherits neuronal matrix perturbed with some mutations after birth (action ‘divide’). Each agent is characterized by affinity marker: 3-dimentional vector which coordinates can take possible integer values in [–2, 2] interval. Agents are considered as relatives if Euclidean distance between theirs markers are less than 0.2 threshold.

Probability to be succeed in attack is equals to ratio of victim’s and attacker’s accumulated energy.

Agent’s actions are categorized and vector of agent strategies is generated using the methodology firstly presented in [2]: to show agent 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, agent’s relative affinity. Thus, agent is being stressed with six input test vectors and then strategy vector was generated according to his reaction (Table 2). For example, strategy ‘020202’ is typical hawk strategy: regardless of internal agent energy level, he will attack any stranger in his area and make no harm to relatives. See agent’s population dynamic in Fig. 1. Population downfall is caused by conflicts between different culture groups.

Table 2. Vector of agent’s strategies. Where a ϵ {0: “rest”, “eat vegetation”; 1: “escape”; 2: “attack”; 3: “divide”}, $i = 1, 2, 3, 4$

Low resource, $r = 0{,}02r\max$		Half of resource, $r = 0{,}5r\max$		Many resources, $r = 0{,}98r\max$	
Relative behind	Non-relative behind	Relative behind	Non-relative behind	Relative behind	Non-relative behind
A_i					

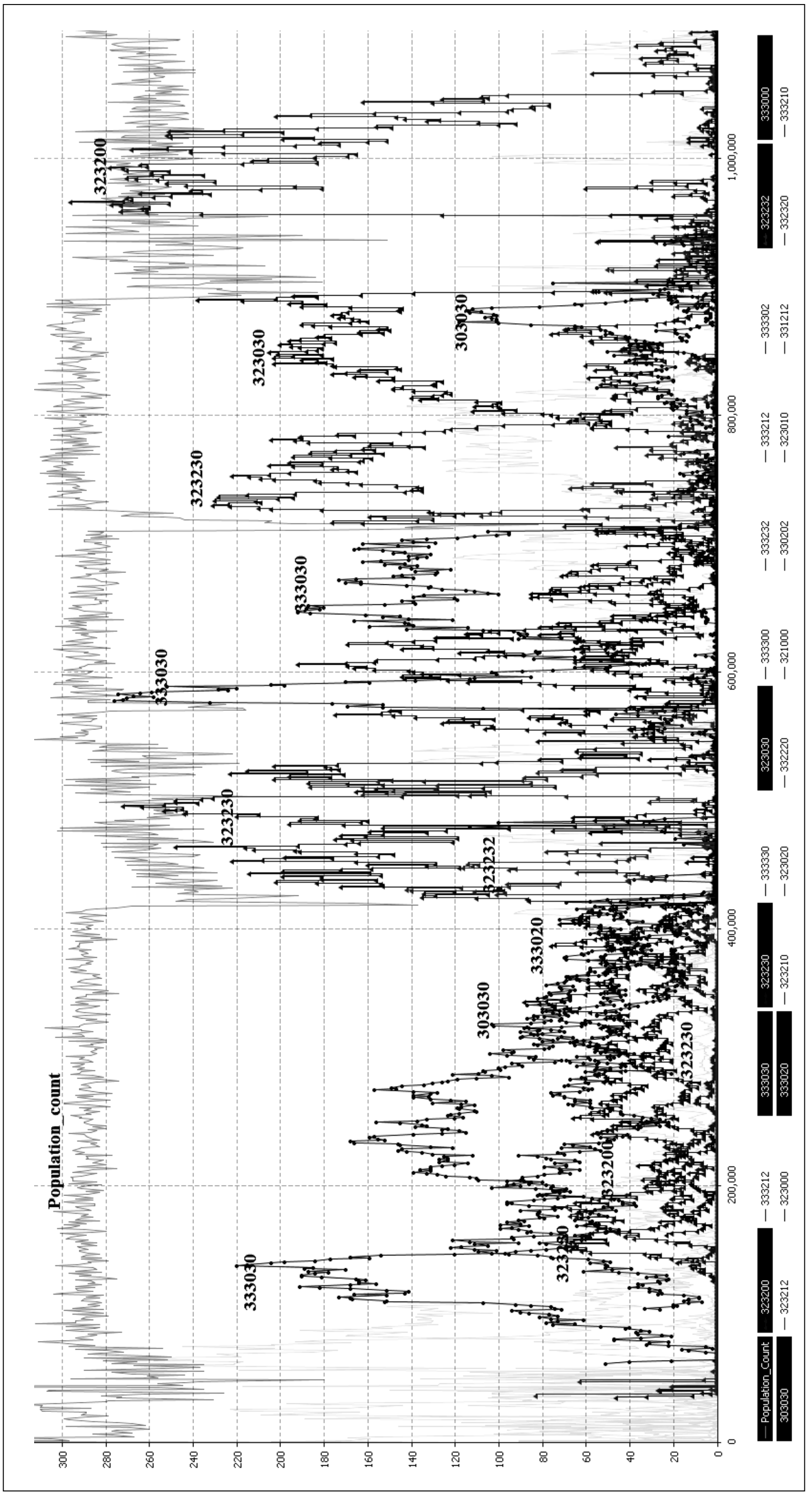


Fig. 1. Population rate (“Population_count” curve) and agent’s strategies

Space. Space is continuous and 2-dimentional. Agent's position is defined with real coordinates (x, y). Space is logically divided on cells (Fig. 2), agent can overcome one cell by two time series with average speed. Agent can perform actions with object on distance closer than Action Radius. Agent is aware of all objects that are located in cells that bear to his cell. New vegetation is randomly appears in space with each time series.

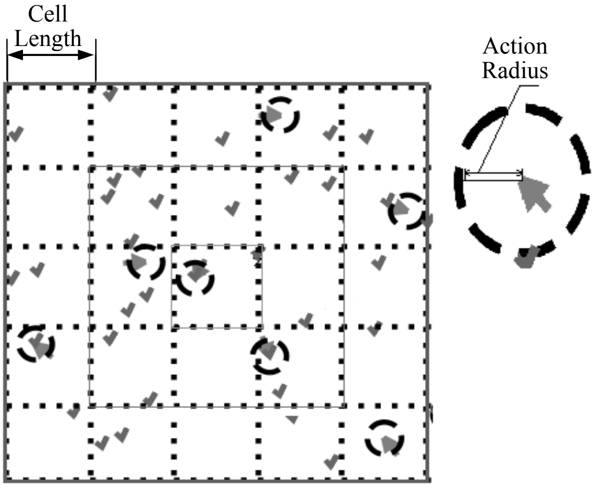


Fig. 2. Agent's space. Agent are presented with arrows, vegetation as checks

For heterogeneous space vegetation checks appears in some areas more frequently that in others (see Fig. 3).

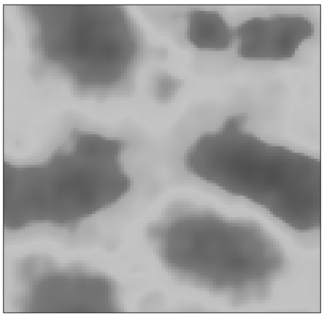


Fig. 3. Example of the map of heterogeneous space

ANALYSIS

Population Genotype Centroid. In addition to presenting phenotype as behavior strategies in current work method of tracking Population Genotype Centroid was used [2]. Consider genotype space G, its dimension equals to number of genes for each agent from population P (quantity of elements in agent's matrix of neural network — $W_{n \times m}$). Let genotype of agent A be $g \in G$, each element of g: g_k, $k = 1, \ldots, nm$ corresponds to element of the matrix W: w_{ij}, $i = 1, \ldots, n$, $j = 1, \ldots, m$. Thus, g defines the point in space G that corresponds to agent A. We should track its centroid C^p to analyse the movement of the whole agent's population cloud:

$$C_i = \frac{1}{N} \sum_i^N g_i .$$

Centroid trajectory can be maintained for a long time in some compact area (gravity field) of the space G, form closed curves corresponding to a specific period cycles, accidentally wander around space or jump from one area of attraction to another. To identify patterns in these behaviors the following characteristic is used [2]:

$$d(t,T)=\sqrt{\sum_i^N (C_i(t+T)-C_i(t))^2} \qquad (1)$$

Expression (1) gives the distance between the centroid locations at time t and $t+T$ [2]. Visualizing of dynamics of values $d(t,T)$ for different values of period T can get an idea of the character of centroid movement in space. For example, in case of random walk of centroid in space $d(t,T)$ will increase with increasing T (Fig. 4,*a*) If for some period of time centroid moves along a closed trajectory of period T_c, then during this period of time the value of $d(t,T_c)$ will be close to zero. Other examples of such visualization shown in Fig. 4.

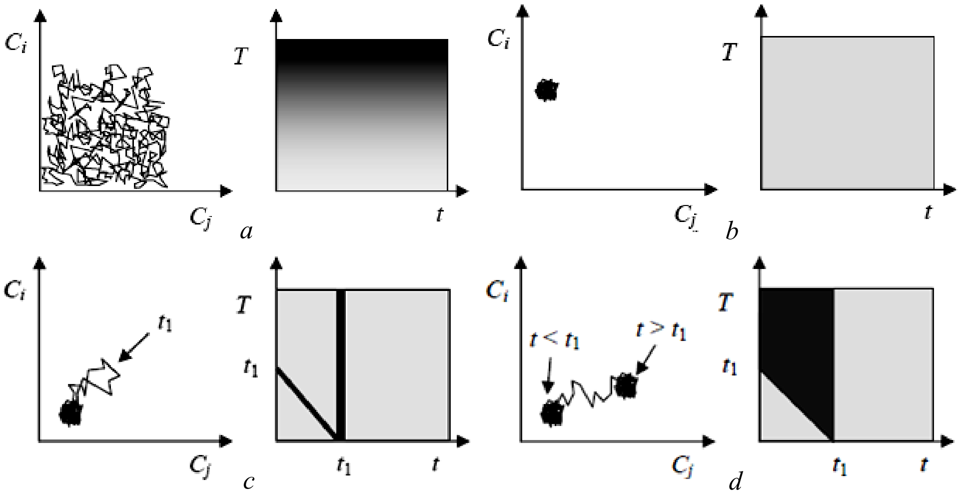


Fig. 4. Example of the different centroid behavior dynamics and visualization of $d(t,T)$ characteristic. Figures are taken from [2]

In the context of the model considered in this paper genotype is a low-level rule for behavior — he abstract specification for agent — that then participates in local interaction of a large set of other types of behavior. Phenotype is the behavior patterns in time and space that develop from these non-linear, local interactions [2] (Fig. 5).

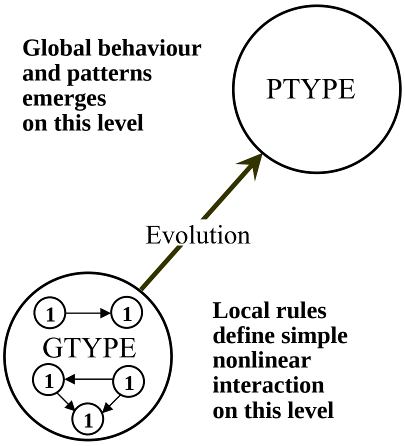


Fig. 5. Interaction of genotype (GTYPE) and (PTYPE) [8]

MAS BEHAVIOUR

Mutli-agent system display variety of different scenarios of agent interactions: predator-prey cycles [2], [13], [5], competition between different behaviour strategies [1], [5], quasi-stable domination of certain strategy for a long period of time or intense variability of strategies.

Let us show competitive interaction between behaviour strategies with similar behavior. Refer to Fig 1 we can see that in some time series population dramatically decreases (for 410, 700, and 900 thousands time series). Considering successful attack actions time series (Fig. 6) we can infer that aggressive competition was taking place for this cases.

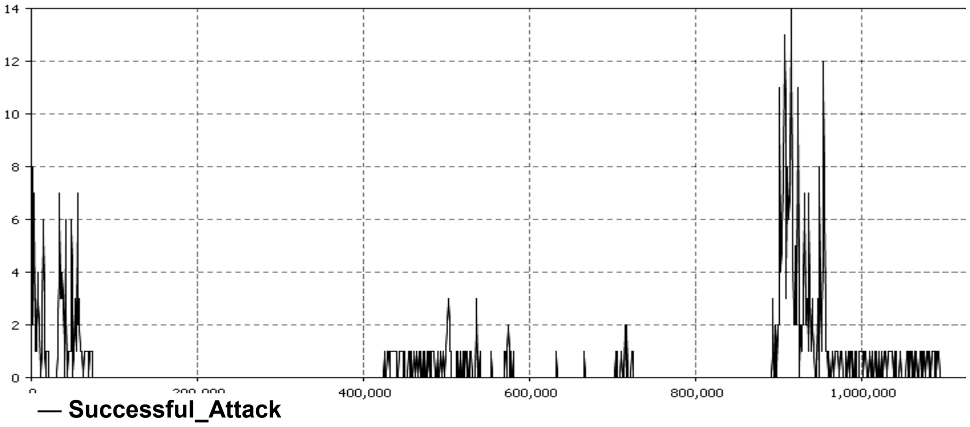


Fig. 6. Successful attack actions count for experiment from Fig. 1

Consider fist crisis episode: population decrease near 400 thousands time series (Fig. 7) — we can see coexistence of the almost similar strategies: "333020" and "333030", the main and crucial difference between them is that first strategy provides aggressive actions to relative agents. Time passed leads to extinction of aggressive non-cooperative strategy.

On the visualization of centroid dynamic (Fig. 8), we can see that all popula-

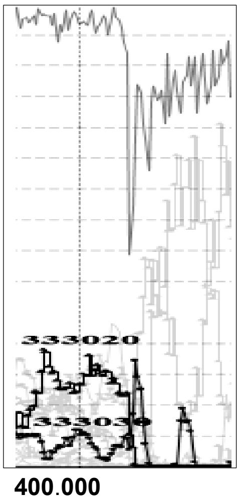


Fig. 7. Detailed fragment from Fig. 1 view. Competitive interaction between strategies with similar behaviour. "333020" — triangles, "333030" — circles

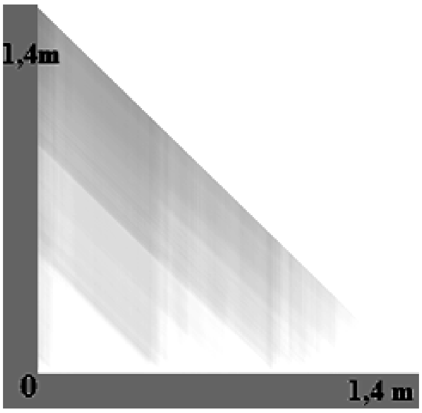
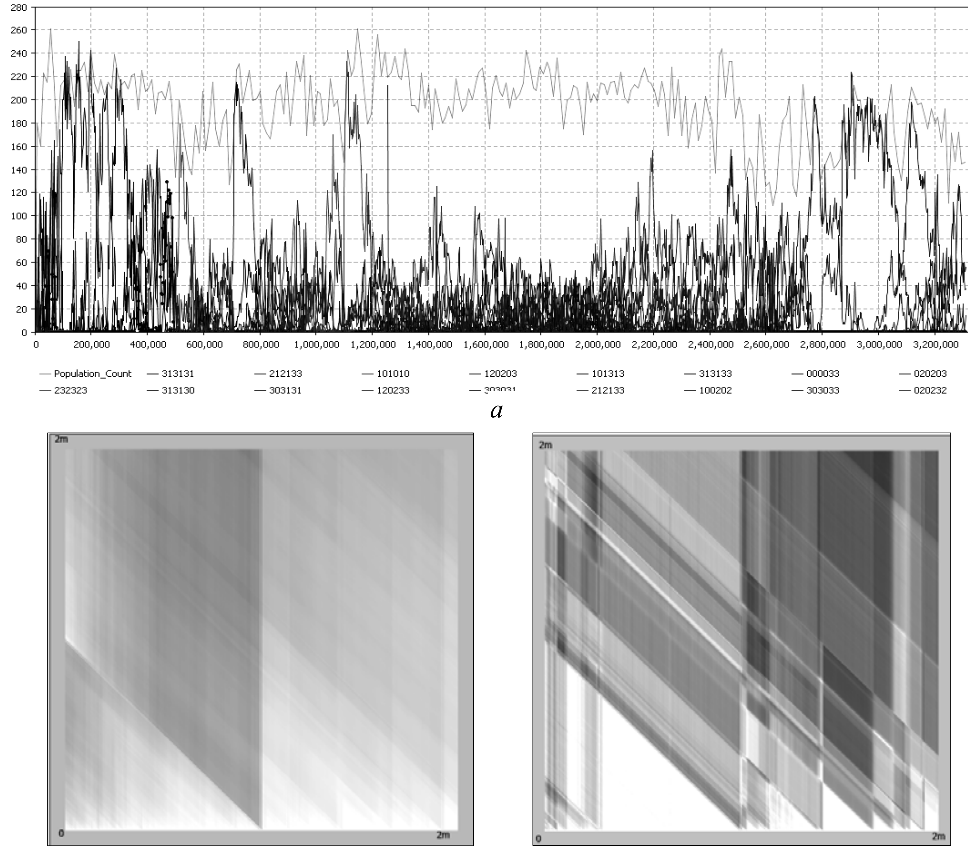


Fig. 8. Visualization of $d(t,T)$ characteristic for centroid behavior dynamics for experiment from Fig. 1

tion crisis periods are accompanied with centroid transition from one area of attraction to another (similar to Fig. 4,*d* dynamic).

However, it is not clear enough whether centroid relocates from one state to another under aggression actions or under peaceful assimilation of agents, such cases were described other models [2].

Culture marker and genotype vector. Let us emphasize on interconnection between genotype vector and vector of relative affinity. Consider two experiments with various behaviour strategies dominate in different periods of time (Fig. 9 and Fig. 10).

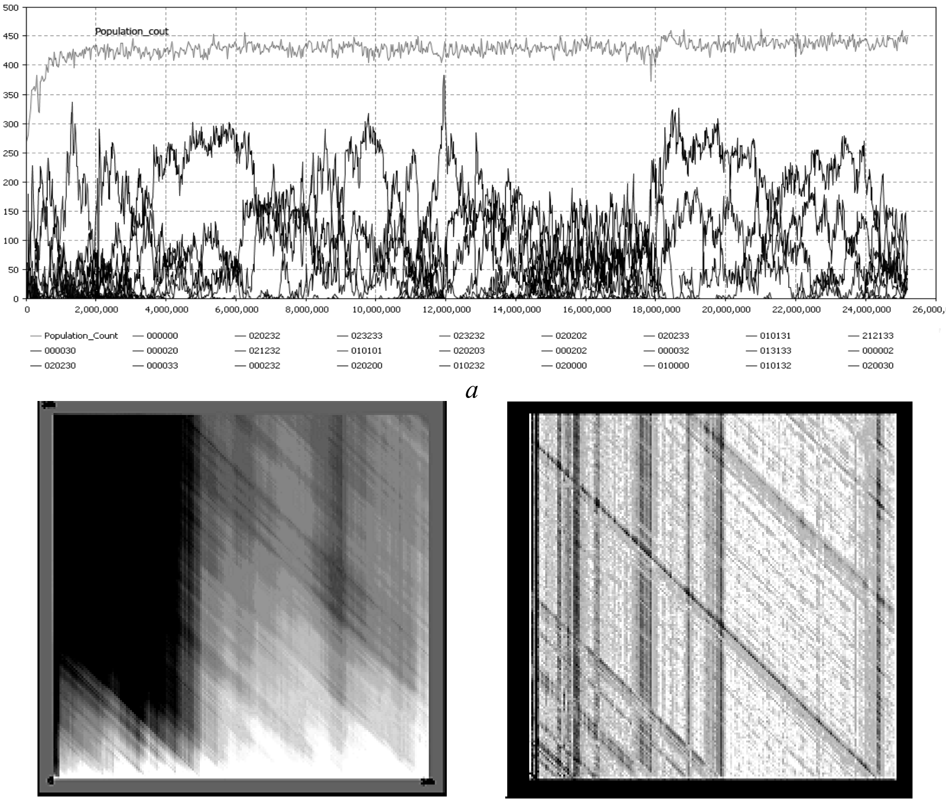


a

b *c*

Fig. 9. Experiment with correlated transition of genotype and culture marker centroids: *a* — strategy series; *b* — genotype centroid transition dynamic visualization; *c* — marker of culture features dynamic visualization

As we can see for the first experiment culture marker centroid dynamic is closely connected (Fig. 9,*b* and Fig. 9,*c*). Culture centroid even has additional transitions from one area of attraction to another. But, for the second experiment no significant culture marker centroid transitions were tracked unlike to genotype centroid dynamics (Fig. 10,*b* and Fig. 10,*c*). Such behaviour causes new questions like dependency of centroids transitions from culture transition between agents and culture marker dimension (as dimension was stated important parameter in [8]), formation of agent groups settlement in different areas and possible swarmlike behaviour, indicate and observe the crucial for transition components of agent's genotype vector, provide clearness in stating of aggressive or peaceful (assimilative) centroid transition.



a

b *c*

Fig. 10. Experiment where transition of genotype and culture marker centroids are not corresponded: *a* — strategy series; *b* — genotype centroid transition dynamic visualization; *c* — marker of culture features dynamic visualization

DISCUSSION

In the work we presented own variation of common model of digital ecology and demonstrated dynamics both of phenotype and genotype agent groups. The formation and further extinction of culture groups caused ether by aggressive predator-prey interaction or by competition of strategies with antagonistic or similar behavior. The following issues are important for further development of the model:

- building new tools for analysis of agents population to enlighten how different interactions affect on group formation and its persistence;
- determine influence of aggressive behavior and genetic transition to the change in the dominance of one strategy over the other;
- analysis of agent group formation and its coevolution;
- introduction of new types of interaction between agents.

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