BIO Web of Conferences **84**, 02015 (2024) https://doi.org/10.1051/bioconf/20248402015
AQUACULTURE 2023

Principles of ontophylogenetic development of artificial general intelligence systems based on multi-agent neurocognitive architectures

M.I. Anchekov[1], *A.Z.* Apshev[1], *K.Ch.* Bzhikhatlov[1], *S.A.* Kankulov[1], *Z.V.* Nagoev[1], *O.V.* Nagoeva[1], and *I.A.* Pshenokova[1]

[1] Kabardino-Balkarian Scientific Center of the Russian Academy of Sciences, 360000 Nalchik, Russia

Abstract. The purpose of the study is to study the possibilities of multigenerational optimization of behavior control systems for agents of general artificial intelligence capable of independently solving a universal range of tasks in a real environment. The main principles of ontophylogenetic synthesis of control systems for agents of general artificial intelligence based on multi-agent neurocognitive architectures have been developed. Methods and algorithms for synthesizing the phenotypes of control systems of intelligent agents according to their genotypes are proposed. A software package for simulating the processes of ontophylogenetic synthesis of multi-agent neurocognitive architectures has been developed and experiments have been carried out to create phenotypes of intelligent agents based on them. A complex genome of an intelligent agent has been developed, the features of a multichromosome genetic algorithm for organizing calculations in the paradigm of multigenerational optimization of multiagent neurocognitive architectures have been established and substantiated. It is shown that multigenerational optimization of the multi-agent neurocognitive architecture of intelligent agents can contribute to the achievement of adaptive resistance to the operating conditions of a general artificial intelligence agent, provide the synthesis of its suboptimal structural and functional scheme, accelerate learning and algorithms for finding solutions to a universal range of problems solved by this agent in its ecological niche.

1 Introduction

Today the problem of creating so-called systems General artificial intelligence (Artificial General Intelligence) is one of the most urgent problems of applied informatics and, at the same time, one of the key unresolved problems of theoretical informatics.

In [10, 13], the theoretical foundations for the creation of artificial general intelligence systems based on the formal apparatus of multi-agent neurocognitive architectures are given. Of course, this theory, at least until an operating system of general artificial intelligence is created on its basis, does not give grounds to believe that even with the help of such a powerful apparatus, this fundamental scientific problem has been resolved today. However, it creates the prerequisites for, in full accordance with the ideas of functionalism, to reduce the thought processes in natural and artificial systems of general artificial intelligence to one design metaphor and to a single computational abstraction.

An intelligent agent immersed in its ecological niche (in the real environment) acts as such a design metaphor, and computational abstraction is a control system for such an agent, the main task of which is to synthesize its behavior in this ecological niche. This behavior is aimed at maximizing the objective function of energy, considered as a measure of the ability of an intelligent agent to implement changes in the real environment.

An intelligent agent is immersed in a real environment with the help of its sensors and effectors. Flows of unstructured data produced by sensors form the basis for identifying the states of the "intelligent agent-environment" system, which are further attributed by the increment values of the objective function using the state labeling function. The synthesis of the behavior of an intelligent agent is generally aimed at the transition from less energetically favorable to more energetically favorable states.

A mathematical abstraction of the synthesis of the behavior of an intelligent agent in a real environment is the proactive construction of a path to the planning horizon in a dynamic decision tree, suboptimal according to the criterion of maximizing the objective function, provided that it does not fall into the so-called. terminal states characterized by zero values of the objective function.

If we take the above design metaphor and computational abstraction as a basis, then in the case when the artificial intelligence system is able to identify the states of the “agent-environment” system similar to the states identified by the natural intelligence system, it can be assumed with some assumptions that both systems work in the same ecological niche and perform a similar function - the synthesis of behavior aimed at solving the problems of the spectrum universal for a given ecological niche by transitioning to more favorable (target) states of this system. The problem, in this case, is understood as the perceived need to change the current state of the "intelligent agent-environment" system to one of such future target states.

However, the problem lies in the fact that the environment for the functioning of a general artificial intelligence system is, by definition, the so-called. real environment, which is characterized by such complex conditions for solving problems as unstructured, uncertainty, stochasticity, dynamism, episodicity, partial observability, activity, etc. In such an environment, the task of synthesizing the suboptimal behavior of an intelligent agent is characterized by gigantic dimensions of the configuration space, which causes difficulties in constructing the space of alternatives in the search problem over a dynamic decision tree and, accordingly, imposes significant restrictions on the ability of an intelligent system to find solutions to problems in an acceptable time, sets the highest requirements for volume of calculations.

In this regard, based on the "natural" analogy, the possibility of ontophylogenetic methods and algorithms to achieve a balance of the optimal ratio of the computational load required to find a solution to the problem between individual individuals in the generations of the population is actualized. The question arises - if the computational abstractions and metaphors of designing natural and artificial intelligent agents are uniform, which makes it possible to implement the ontological learning paradigm in the general artificial intelligence system, then is it not advisable to complete the analogy by providing the artificial intelligent agent with opportunities for genetic (phylogenetic) learning? Phylogenetic (multi-generational, evolutionary) learning in this case is understood as a change in the composition and structure of all levels of nesting of a multi-agent neurocognitive architecture based on a genetic algorithm in the interphase of the generation change of intelligent agents.

The purpose of the study is to study the possibilities of multi-generational optimization of control systems based on multi-agent neurocognitive architectures to create general artificial intelligence agents capable of independently solving a universal range of tasks in a real environment.

The object of research is the processes of ontophylogenetic synthesis of control systems for software agents of general artificial intelligence.

The subject of the study is the basic principles of achieving adaptive stability of general artificial intelligence agents based on multi-agent neurocognitive architectures to operating conditions (environmental conditions), algorithms for synthesizing optimal structural and functional schemes of such intelligent agents, the principles of ontophylogenetic learning in the process of synthesizing problem solving over dynamic decision trees.

The main objectives of the study:

- development of the main principles of ontophylogenetic synthesis of control systems for general artificial intelligence agents based on multi-agent neurocognitive architectures;
- development of the basic principles of multigenerational optimization of the structural and functional organization of such agents;
- development of methods and algorithms for the synthesis of phenotypes of control systems of intelligent agents according to their genotypes;
- development of a software complex for simulation modeling of the processes of ontophylogenetic synthesis of multi-agent neurocognitive architectures and the implementation of experiments to create phenotypes of intelligent agents based on them.

1.1 Ontophylogenetic Models of Learning

The idea of combining learning based on a combination of ontogenetic and phylogenetic algorithms, having such an effective analogy in the methods of learning natural intelligent agents, has been actively developed during almost the entire period of the formation of evolutionary computing [8, 16]. To designate mixed methods and algorithms for training intelligent agents that combine both of these approaches, we will use the term "ontophylogenetic" (method, algorithm).

To date, the ontophylogenetic approach has received the widest development in terms of multigenerational optimization of the composition, structure, and functional properties of artificial neural networks, forming a whole scientific direction called “neuroevolution” [9]. In [17], ontophylogenetic algorithms with an ontological part based on reinforcement learning are considered.

In [7], neuroevolutionary learning of a cognitive architecture consisting of competing artificial neural networks is considered. In this ontophylogenetic architecture, at each learning step, depending on the change in the rate of convergence of the solution, a choice is made between the ontological and phylogenetic method of parameter modification.

Of considerable research and applied interest are the developments of evolutionarily modifiable multi-agent neural networks [1, 2, 3], in which artificial neurons are represented by software agents that perform calculations based on production rules. For example, in [7], neuroevolutionary learning of a cognitive architecture consisting of competing artificial neural networks is considered. In this ontophylogenetic architecture, at each learning step, depending on the change in the rate of convergence of the solution, a choice is made between the ontological and phylogenetic method of parameter modification.

Based on the concept of the calculator's agency, when an intelligent agent immersed in a certain environment is chosen as a metaphor for designing a decision-making system, a whole direction has been formed, called Artificial Development, in which ways to obtain phenotypes of individuals with the so-called. indirect coding, i.e. in a situation where the population formed as a result of iteration of the genetic algorithm consists of individuals that, in order to achieve the calculated state in which they will be used to solve problems, must additionally go through the ontological development of the phenotype [6].

This direction is closely connected with such an already vast area of theoretical computer science as Artificial Life, since the period of the ontological development of the phenotype is precisely the period of the artificial life of an individual (agent). To date, a great variety of variants of such phenotypes for the conditions of application in solving various problems has been developed. All of them are united by the presence of a certain ecological niche (a habitat in which the states of an agent are marked by increments of the objective function of this agent), a homeostatic control system, and a decentralized, multi-agent nature [6, 18].

For example, in [5], an ontophylogenetic cognitive architecture is described, which is a rational agent of artificial life that synthesizes behavior in a simulated environment. The choice of actions is carried out by agents based on the analysis of the states of the "agent-environment" system using production rules. Genes encode the structure and transitional functions of cognitive nodes. The fitness function of the genetic algorithm is related to the ability of agents to win in the simulation of natural selection in a simulated environment.

In [4], the ontophylogenetic approach is applied within the paradigm of developing robots (Developmental Robotics). A genetic algorithm that modifies the cognitive architecture that synthesizes the behavior of a real robot allows it to solve target problems in a real environment, permanently adapting to changing conditions.

The ontophylogenetic approach makes it possible to implement a more flexible strategy for solving the problems of synthesizing the behavior of intelligent agents based on a combination of ontological and genetic search methods, taking into account the specifics of the meaningful meaning and configuration of the search space.

In general, ontophylogenetic approaches to the synthesis and training of intelligent agents based on cognitive architectures are still developed and studied very little, despite the obvious promise of this direction.

The relevance of the study is determined by the need to develop an ontophylogenetic approach for the development of the theory and practice of creating intelligent decision-making and control systems (intelligent agents) of general artificial intelligence based on multi-agent neurocognitive architectures that are distinguished by a high degree of structural and functional similarity to natural intelligent agents.

In the case of an intelligent agent control system based on a multi-agent neurocognitive architecture, the task of forming an ontophylogenetic basis for development and learning becomes much more conceptually complicated. One of the reasons is the already mentioned close analogy of such intelligent agents with “natural” intelligent agents, which creates the prerequisites for the predominant use of multi-agent neurocognitive architectures to solve the problem of creating artificial general intelligence systems.

In addition, the multi-agent neurocognitive architecture, as a rule, is a simulation model of a multicellular biological organ - the brain, consisting of individual neuron cells, which themselves, in turn, consist of active internal constructs - organelles. The structural and functional properties of the latter also depend on the composition and relationships of the active elements that form them - protein macromolecules, which, in turn, are also complexly structured on the basis of individual constructs, such as amino acids, sugar bases, etc. These minimal structural and functional elements are already directly encoded by gene-determined processes, but they arise not as a result of some ideal ("instantaneous") synthesis (as, for example, in genetic algorithms), but as a result of a dynamic system-wide diachronic epigenetic process of gene expression.

A whole group of questions arise. Is it necessary to model the multicellular structure of an organism? What is the minimum structural and functional unit in this case that influences the processes of behavior synthesis by an intelligent agent? Are separate genomes required for each minimal structural-functional unit? What information should genes contain? What format should they be? What should be the structure of the genome, the structure of the genotype of an intelligent agent?

Should gene expression be modeled as a dynamic epigenetic diachronic process? At what level of structural nesting of a multi-agent neurocognitive architecture should it be modeled? How and with what feedback to manage this process?

Another significant question is whether and to what extent the knowledge gained as a result of ontological learning of an intelligent agent should be involved in the process of phylogenetic learning? If, for example, an intelligent agent built on the basis of indirect coding according to its genotype, having passed the minimum basic period of individual development, during which the algorithms of both ontological and phylogenetic learning were involved, having reached the design functionality, is not able to solve some problem. Then, as a result of the implementation of several attempts, on the basis of further ontophylogenetic training, this intelligent agent at some point in time synthesizes a solution to this problem and in the future always effectively solves it. The question is, should a new genotype of an intelligent agent be formed based on the data of the multi-agent neurocognitive architecture formed in the previous training period? Presumably, this way of learning, let's call it bidirectional ontophylogenetic learning, of an intelligent agent can be extremely effective.

The second related question is whether the current intelligent agent should be eliminated, or whether a population with mixed (even if related) genotypes should exist in the future?

We will try to give brief answers to these highly debatable questions, based on the prospect of creating a software agent for general artificial intelligence based on a multi-agent recursive neurocognitive architecture.

2 Materials and methods

Intelligent agents under the control of multi-agent neurocognitive architectures adapt to environmental conditions by learning, which consists in changing the composition of neuron agents (agneurons) located in the nodes of the cognitive architecture (Fig. 1a), as well as the connections between these agneurons. Agneurons are rational software agents that also maximize the target function of energy, can exchange messages with each other and conclude with each other the so-called. contracts for the exchange of information and energy. The substantive meaning of such a contract lies in the formation of an associative connection between two agneurons, which describes a certain relationship between the states of the “intelligent agent-environment” system, the functional representation of which in the multi-agent neurocognitive architecture is performed by these two agneurons. The agneurons themselves also contain within themselves a multi-agent cognitive architecture, in the functional nodes of which the so-called. actors are software agents that are not rational, since they do not have their own objective function (Figure 1b). Figure 1 shows images of the elements of the multi-agent neurocognitive architecture, obtained using the program we developed for simulating artificial general intelligence systems.

Actors operate under the control of their own knowledge bases containing knowledge presented in the form of production rules, the antecedent parts of which consist of logical clauses that identify another actor - the sender of the message and the message itself, and the consequent parts contain instructions for sending specific messages to other actors by this actor. [14, 15].

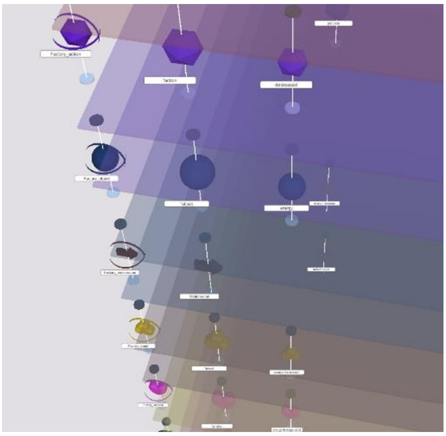

Fig. 1a. Multi-Neuron Neurocognitive Architecture of an Intelligent Agent

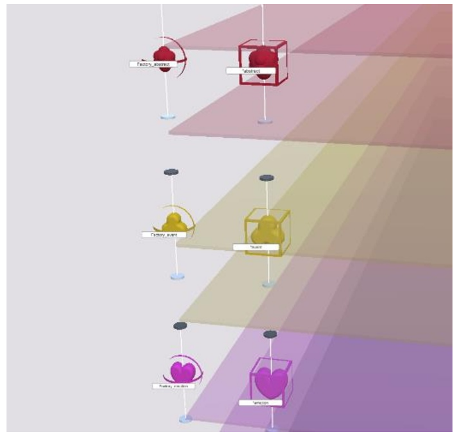

Fig. 1b. Multi-actor cognitive architecture of the agent-neuron

Thus, we can conclude that the multi-agent neurocognitive architecture is recursive, allowing the nesting of multi-actor cognitive architectures in the composition of agneurons. Moreover, the cognitive architectures of the upper and lower levels, in general, repeat each other in terms of the composition of cognitive nodes. This composition is called the invariant of the multi-agent cognitive architecture [11] and includes the cognitive nodes of event recognition (state identification), state evaluation, goal setting, action synthesis, which, working sequentially, provide the synthesis of states and actions necessary for proactive path building in a dynamic decision tree. Figure 1 shows these cognitive nodes for both the intelligent agent (consisting of agneurons) and agneurons (consisting of actors). For their designations in the visualization, three-dimensional pictograms (graphic models) of various shapes are used. We use the same graphical models of 3D pictograms of agents belonging to functionally similar nodes of the multi-agent cognitive architecture invariant for 3D pictograms of agneurons and actors. The only difference is that in the 3D actor pictograms, these graphical models are inscribed in the contours of parallelepipeds (Figure 1). To designate the agents of the cognitive node of event recognition, a three-dimensional pictogram in the form of a ball is used - they perform a functional representation of the observed objects (agent-objects - agneurons-objects, actor-objects), a polygon (agent-actions), a three-dimensional shamrock (event agents), a "heart" (agents for evaluating states), a three-dimensional “flag” (goal-setting agents), a three-dimensional arrow (agents for synthesizing actions) (Figure 1).

The key method of training the above-described intelligent agents is to change the composition of agneurons and actors, the structure of connections and types of relationships between them based on the algorithm of ontoneuromorphogenesis previously developed by us [12], which controls these changes in accordance with the principles of brain neuroplasticity. The essence of this algorithm is that the so-called. axo-dendronal connections, which serve as associative links between agneurons, grow between those of these agneurons that are statistically often excited (pass into a state of active signal processing) at the same time. These connections are shown in Figure 1 by lines directed from the axons (located at the top of the 3D pictograms) of some agneurons to the dendrites (located at the bottom of the 3D pictograms) of other agneurons. Here we use the well-known Heb learning principle, however, in multi-agent neurocognitive architectures, its application takes into account structural limitations - associative contracts can only enter into certain types of agneurons.

The method of ontoneuromorphogenesis demonstrates the features of the ontogenetic method in the sense that it manifests itself during the active functioning (time of "life"), being (gr. ontos) of an intelligent agent. At the same time, it is also a phylogenetic method, since the directed growth and degradation of connections between agneurons occur on the basis of the activation of the genomes of these agneurons under certain environmental conditions.

As can be seen in Figure 1a, the neurocognitive architecture consists of levels, the so-called. neurocognitons [15], which are functional units of the neurocognitive architecture containing various types of agneurons. The agneurons within neurocognitons in Figure 1a are depicted in "narrower" layers, followed by "wider" layers, in which messages are visualized sent by agneurons of some types (contained in neurocognitons of certain types) to agneurons of various other types based on the information contained in the so-called. multi-agent knowledge bases as part of actors that form a multi-agent (multi-actor) cognitive architecture built into agneuron (Figure 1b).

The multi-actor cognitive architecture, in turn, consists of actorcognitons containing actors in their composition. Structurally and functionally, neurocognitons and actorcognitons correspond to the above-described functional units of the multi-agent cognitive architecture invariant.

Actors differ from agneurons in that they do not have their own objective function and work on the basis of procedural algorithms specified by production rules of the above type.

The structure and composition of actorcognitons and neurocognitons can vary depending on the type of agneuron (phylogenetic differences) and its experience, formed on the basis of ontological learning. In general, the task of a multi-actor cognitive architecture is to synthesize the behavior of an agneuron, and the task of a multi-neuron cognitive architecture is to synthesize the behavior of the entire intelligent agent. Therefore, the structure and composition of cognitons (actorcognitons and neurocognitons) in the general case is formed in such a way that they include such agneurons and state recognition actors in the “agent-environment” system (intelligent agent-environment, agneurons-environment), estimates of these states in terms of the increment values of the utility function of the corresponding levels, the choice of target states, the synthesis of actions that, on the basis of their coordinated work, synthesize the desired target states and transfer the intelligent agent to them.

Agneurons as part of the multi-agent neurocognitive architecture of an intelligent agent are motivated to interact with each other on the basis of a utility function, the meaningful meaning of which is associated with an increase in the agent's energy during the transition to the target states of the "agent-environment" system based on the agent's synthesis of its behavior in this system.

The need to synthesize its behavior is determined for agneuron by low current values of utility (energy) and information (knowledge) that these values can be significantly increased upon transition to certain states of the “agneuron-environment” system in the future. Since the environment for an agneuron is a multi-agent neurocognitive architecture of an intelligent agent with all its neurocognitons, and this agneuron cannot receive an increase in the utility function (energy) in any other way than from other agneurons, the desired target states for this agneuron are always associated with receiving a reward in the form of "portions" of increments of energy from other agneurons.

Agneurons can send some of their energy to other Agneurons for the purpose of acquiring ("buying") some information they need. In turn, having received the necessary information, agneurons can, with the help of their internal multi-actor cognitive architecture, form some “own” information, which can also be of value to other agneurons, and, after executing a multi-agent negotiation algorithm, transfer (“sell”) this information to these agneurons, accordingly, having also received some reward for this in the form of a certain number of portions of energy.

Thus, when a multi-agent neurocognitive architecture of an intelligent agent performs the synthesis of a behavior plan, multiple chains of interactions of agneurons with each other are formed, built on the mechanism of information exchange for energy. Ultimately, after the desired plan is synthesized and executed, the intelligent agent passes into some new state. If, as a result of such a transition, an intelligent agent acquires additional energy from the environment, then this reward, using the involved contracts between neurons, is distributed along such chains, which allows agneurons to maintain the energy level at the required level and motivates them to further interaction.

Thus, the dynamic decision tree of an intelligent agent is synthesized by agneurons based on multi-agent cooperation. At its vertices, there are states of the "intelligent agent - environment" system, and the arcs are marked by the actions of the intelligent agent and the environment (Figure 2). For example, the figure shows that for the transition between the states $S_{t_c}^{ij}$ and $S_{t_c}^{ih}$, the i-th intelligent agent performs the actions $A_{t_c}^{ijk}$, and the environment performs the actions $W_{t_c}^{ijk}$.

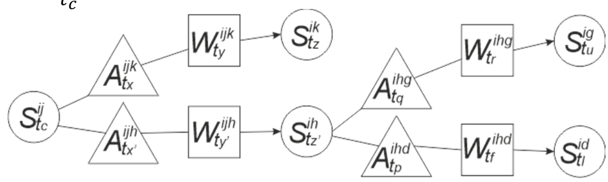

Fig. 2. Structure of a dynamic decision tree intelligent agent

In turn, the vertices of the agneuron dynamic decision tree represent the states of the agneuron-environment system, and the arcs, respectively, are marked by the actions of the agneuron and the environment, which is a collection of all other agneurons that are part of this intelligent agent.

Of fundamental importance for the purposes of this study in this case is the fact that in order to build a global path (the behavior of an intelligent agent), suboptimal according to the criterion of maximizing the target function of energy, you must first build a set of local paths (behavior of agneurons), which are suboptimal according to local criteria for maximizing their target functions energy. Thus, each structural element of the general artificial intelligence agent simulation model, starting from the level of actors, contributes to the search for a solution to the original problem. This, in particular, means that the combination of ontological and phylogenetic learning should start from the minimum (lowest) level of a recursive multi-agent neurocognitive architecture, the structural elements of which are already involved in solving search problems. Therefore, already at this minimum level, encoding of hereditary information should be performed.

Since the behavior of an agneuron is synthesized on the basis of multi-agent algorithms performed by the actors in its composition, and the actors perform their functions on the basis of production rules that are in their knowledge bases, it is likely that the genotype of an intelligent agent should provide the possibility of parametric variability in the composition and content of the knowledge of the actors, structures of agneurons and structures of intelligent agents.

The behavior of actors depends on the composition and content of the rules. The behavior of agneurons does not depend directly on the rules, since agneurons do not have their own rules. It depends on what types of actors and what kind of actors are included in its composition, as well as on the structure and meaningful meaning (functional topology) of the contracts concluded between the actors as part of this agneuron.

Similarly, the behavior of an intelligent agent is not directly described by any rules that would be stored in a separate knowledge base of an intelligent agent - its behavior depends on what types of agneurons and what agneurons are included in it, as well as on the functional topology of contractual links between them.

Therefore, by modifying the rules of actors, the structure and composition of actorcognitons inside agneurons, as well as the structure and composition of agneurons inside the multi-agent neurocognitive architecture of an intelligent agent, it is possible to control the functional properties of local search processes and, ultimately, the global process of finding solutions.

Thus, the minimum structural and functional unit that influences the processes of behavior synthesis by an intelligent agent is a single clause of the production rule of the actor's knowledge base. Since each actor in a certain agneuron belongs to a certain type and occupies a certain place (in order, in terms of functionality) in the actorcogniton of this agneuron, it is, in this sense, unique and therefore requires its own separate genome.

Obviously, each agneuron must also have its own genome. It should consist of the genomes of the actors included in this agneuron and some additional information. Accordingly, using an analogy from biology, we will call the hierarchical complexly structured genome of an intelligent agent a genotype and consider that it consists of the genomes of all agneurons included in this intelligent agent, including the genomes of all its actors, and some additional genetically significant information.

3 Theory

The actor's genome, in addition to information about each clause of each rule of the actor's knowledge base, must also encode information about the contracts of this actor, which must be provided phylogenetically, i.e., must be created in the process of forming the phenotype of an intelligent agent based on the information contained in its genotype , and, in particular, in the process of creating the phenotype of a particular (containing this actor) agneuron according to the genotype of this neuron and, in particular, according to the genome of this particular actor.

Information about the composition of the multi-actor cognitive architecture of a particular agneuron should already be contained at the level of this particular agneuron, i.e. it must be encoded by the agneuron genome. Such information, in particular, includes the structural composition of the actorcognitons of a given agneuron (an indication of which actorcognitons and in what order are included in its composition), as well as the composition of each of the actorcognitons of a given agneuron (an indication of which specific actors are included in its composition). each of the actorcognitons).

In addition, the agneuron genome must also contain information about the structure of contracts in which this agneuron must be involved in the process of initial ontological development during the transition from genotype to phenotype.

By analogy, information about the structural composition of neurocognitons included in the multi-agent neurocognitive architecture of an intelligent agent should contain the genome of this agent. In addition, it must contain information about the composition of specific agneurons in each of the neurocognitons of an intelligent agent.

The question of direct or indirect coding during the transition from the genotype of an intelligent agent to its phenotype is complex. On the one hand, it is clear that from the moment of formation of the genome of a new individual to the moment when this individual is ready to independently enter the arena of natural selection in real nature, some time must pass, which is associated with the effect of physical restrictions on the nature of the growth and development of biological organisms. On the other hand, it is also obvious that such a “delay” leads to the involvement of epigenetic factors in the process of formation of the phenotype of an organism, some of which act as feedback variables in the control system of this process, creating the prerequisites for the genetic variability manifested in a multicellular organism -

deterministic scenarios for the development of the phenotype, ultimately, led to a greater degree of adaptability of the formed organism to specific environmental conditions.

In humans, the period of reaching maturity of the phenotype for independent survival in evolution has undergone a significant lengthening, which is probably due to the need to involve not just environmental, but social factors in individual development. It is also clear that it is the presence of a mixed ontophylogenetic scenario for the formation of the phenotype that makes it possible to fully use these factors precisely for the creation of functional subsystems of the body that provide the synthesis of behavior that is commonly considered intellectual. It suffices to recall here that Mowgli foundlings, for various reasons, having outgrown a certain period of development in childhood, being outside the social environment normal for a person, even being subsequently placed in such an environment, in the future are practically unable to master natural language and socially determined models familiar to us. behavior.

The importance of the socialization process for the formation of a multi-agent neurocognitive architecture capable of providing such behavioral models can hardly be overestimated. The main value of simulating intelligent agents based on such cognitive architectures, from our point of view, lies precisely in the fact that, by immersing such agents in a communicative environment, it is possible to observe the forms and content of the growth and development of these cognitive architectures. Therefore, of course, in the structure of the genome and in the simulation model of artificial development and socialization of an intelligent agent, it is necessary to provide for the possibility of creating, storing and using the information necessary for indirect encoding of the phenotype of this agent, which is realized in the process of its formation during the period of functioning (“life”) of this agent. intelligent agent.

In order to ensure this possibility, we introduce the so-called into the composition of the actors of each actorcogniton and into the composition of the agneurons of each neurocogniton. actor and neural factories - software agents that are able to dynamically "on demand" generate new actors and agneurons during the operation of an intelligent agent. This mechanism allows replenishing the composition of actorcognitons and neurocognitons with new actors and agneurons.

Another mechanism built into the simulation model we are developing allows you to automatically change the structure of actorcognitons and neurocognitons depending on the actual representation of certain types of actors and agneurons in the multiagent neurocognitive architecture. Thus, if in the process of individual development of an intelligent agent it becomes necessary to generate new actors or neurons by an actor factory or neurofactory, the system will automatically complete the composition of actorcognitons and neurocognitons if actors or agneurons of such types were not previously represented in the cognitive architecture.

The third mechanism for managing the development of a multi-agent neurocognitive architecture, taking into account epigenetic factors, is the ability of actors and agneurons to enter into, respectively, situationally determined contracts with other actors and agneurons based on the ontoneuromorphogenesis algorithm. An analogue of the computational abstraction of this multi-agent algorithm for concluding contracts between neurons is the processes of directed growth and degradation of axo-dendronal connections in the brain. This is a typical ontophylogenetic process in which the dormant axon growth control circuit is awakened in the event of certain environmental conditions.

In our model, this mechanism is provided by the rules for the behavior of actors and agneurons of certain types, which are encoded in the genomes of actors and agneurons similarly to other rules governing their behavior.

The structure and functions of actor and neural factories are encoded in the genomes of agneurons and intelligent agents in a similar way. The structure of the developed intelligent agent genotype is shown in Figure 3.

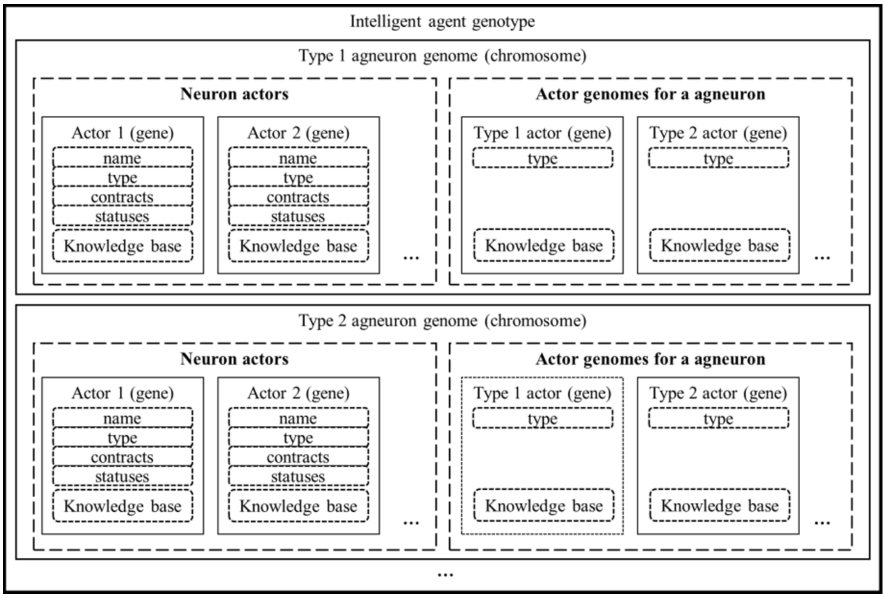

Fig. 3. The structure of the genotype of an intelligent agent

In order to be able to realize the dual ontophylogenetic nature of the processes of growth and development of the multi-agent neurocognitive architecture, the genomes of actors, agneurons and intelligent agents were developed as knowledge bases in JSON format containing production rules, the left, antecedent parts of which identify external and internal triggering conditions products, and the right ones determine the actions that need to be performed to make appropriate changes in the structure, composition and functional topology of the corresponding levels of the multi-agent neurocognitive architecture (Figure 4).

```
  Object: "Agneuron"
  Type: "default"
  id: "{16f4b87e-5962-4ccb-8f6a-5a79f13cac13}"
> ActorCognitons: Array
v ActorGenomes: Array
  > 0: Object
  v 1: Object
      AgentType: "action"
    v knowledgebase: Array
      v 0: Object
          activateIf: "Всегда"
        v currentCondition: Array
          v 0: Object
              From: "Status"
              FromNeuron: "@"
              Max: 0
              Message: "New"
              Min: 0
              Operation: "Between"
              Time: 0
              Type: "Default"
        v desiredCondition: Array
        v ruleAction: Array
          v 0: Object
              Message: "New"
              Time: 0
              To: "RemoveStatus"
              ToNeuron: "@"
```

Fig. 4. Fragment of the epistemological description of the genome

This approach allows for simulation of the expression of the genomes of actor and neuron factories, actors and agneurons throughout the life of an intelligent agent, which, in turn, ensures the permanent development of the phenotype of the multi-agent neurocognitive architecture that controls the behavior of this intelligent agent, also throughout the entire period of his life. .

The structure of the knowledge base of the actor genome is shown in Figure 5.

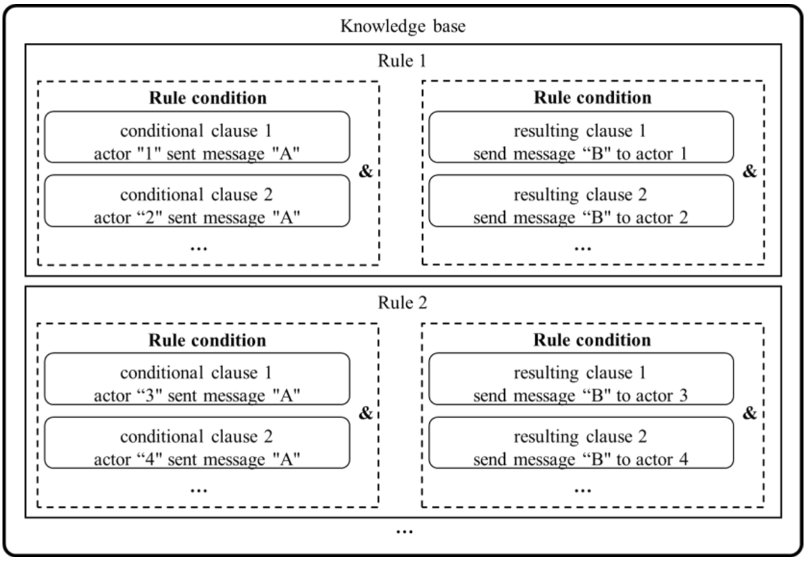

Fig. 5. Structural elements of the actor genome

Thus, the expression of the genes of an intelligent agent is modeled at the levels of the genomes of its actors and agneurons as a dynamic epigenetic diachronic process. Inverse epigenetic relationships are taken into account using production rules that identify the states in which it is necessary to start gene expression, the directed nature of which, in turn, is provided by knowledge interpretation algorithms, in the form of which all genomes in the genotype of an intelligent agent are structured.

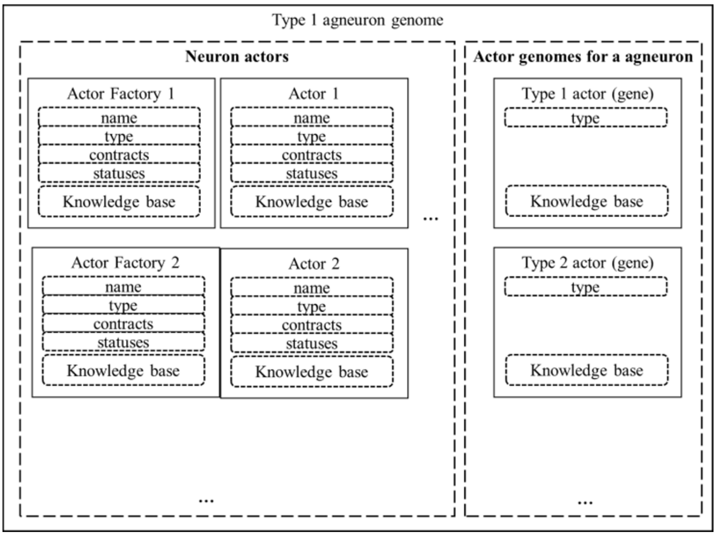

Fig. 6. Agneuron genome

In the general case, it is assumed that an intelligent agent, after immersion in the environment, before starting its functioning directly in the interests of solving target problems, must already be sufficiently formed to perform basic behavior. Therefore, the genotype of an intelligent agent should be arranged in such a way that, when creating a starting phenotype based on it, all the basic functional systems (agneurons, contractual connections between them, actors within agneurons) necessary to perform such behavior would already be formed.

In order to systematically ensure the development of functional systems responsible for the synthesis of the behavior of an intelligent agent in various situations, it is necessary to ensure that the genetic algorithm does not mix genes encoding the structure and composition of actors of various actor cognitons in the multi-actor cognitive architecture of agneurons, as well as genes, encoding the structure and composition of agneurons of various neurocognitons.

To do this, both at the level of actor genomes, and at the level of agneuron genomes, and at the level of the genome of an intelligent agent, there must be several different chromosomes, and they must be responsible for encoding the features of the corresponding functional units (actorcognitons, neurocognitons) at the appropriate levels. Thus, the applied genetic algorithm should be multichromosomal and take into account the multi-agent hierarchical structure of the genotype of an intelligent agent.

Taking into account the fact that the clause of the production rule is the minimum structural and functional unit for controlling the behavior of actors, it should become the minimum coding unit for which one locus of the chromosome is responsible.

Thus, an actor's genome must contain coding loci for each clause of each rule of its starting knowledge base.

In addition, agneuron chromosomes should contain a code for synthesizing the structure and composition of internal actorcognitons, and the chromosome of an intelligent agent should contain a code for synthesizing the structure and composition of neurocognitons as part of a multi-agent neurocognitive architecture.

The scheme of the genetic algorithm applicable for the phylogenetic synthesis of intelligent agents based on multi-agent neurocognitive architectures is shown in Figure 7.

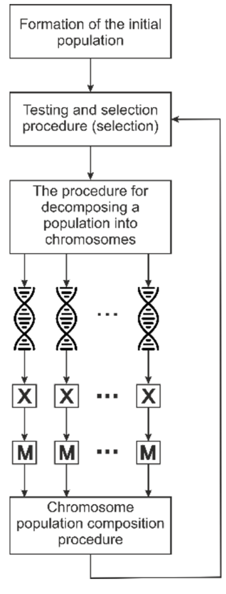

Fig. 7. Multichromosomal algorithm for the exchange of genetic data of intelligent agents: X-operation of crossing-over: M-operation of mutation

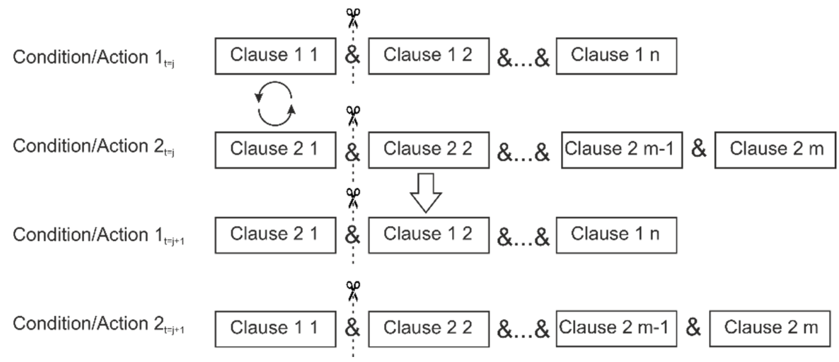

Fig. 8. An example of the implementation of a single-point crossover

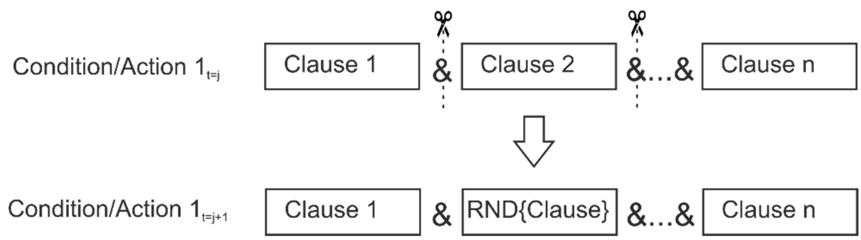

Fig. 9. An example of the implementation of a single point mutation

This genetic algorithm will allow for the exchange of genes between chromosomes along homologous regions, taking into account the possible difference in the length of the chromosomes. In this case, the homology will be aligned with respect to the areas specialized in the formation of individual functional systems of the phenotype being formed. When the genetic algorithm is executed, the exchange of genetic information between the regions encoding various structural and functional subsystems will not be carried out either at the level of actors, or at the level of agneurons, or at the level of intelligent agents.

4 Calculation

In order to study the formed provisions on the structure of the genotype and its relationship with the phenotypes of intelligent agents, using the program for editing such agents developed by us, simulation models of genotypes were built and experiments were carried out to create multi-agent neurocognitive architectures based on them.

In order for an intelligent agent to perform functional tasks, combining phylogenetic and ontological modifications in the process of growth and development of its control multi-agent neurocognitive architecture, starting from the moment of its “birth”, it must be able to maintain its “life” by performing a certain homeostatic cycle. Therefore, by the time of birth, he must have a control multi-agent neurocognitive architecture that provides such basic functionality.

An experiment was carried out to synthesize the phenotype of such an agent based on the developed genotype, which, in addition to the genome of an intelligent agent, also includes the genomes of all agneurons and all actors included in these agneurons. To describe the production rules of the knowledge base that define the genomes of actors and agneurons, data markup in the JSON format was used.

Visualization of the initial phenotype obtained as a result of direct interpretation of data on the genomes of actors and agneurons and other information contained in the genotype is shown in Figure 10.

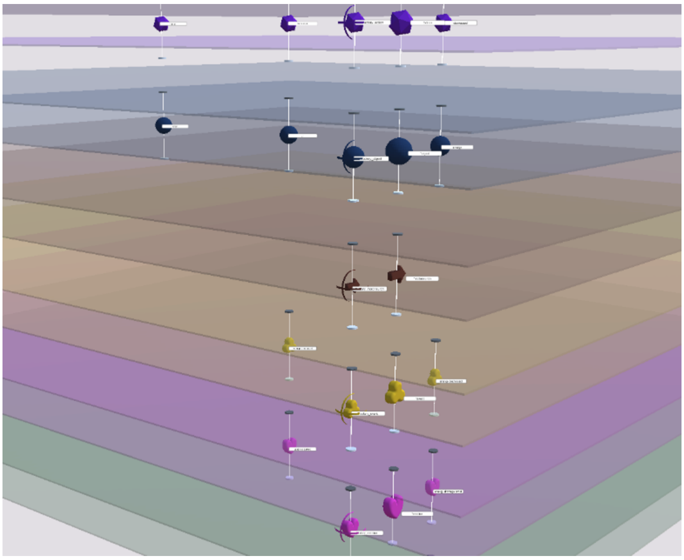

Fig. 10. Initial phenotype of an intelligent agent

Visualization shows that as a result of imitation of phylogenetically determined changes at the stage of "embryonic development", a minimal basic multi-agent neurocognitive architecture of an intelligent agent was formed, containing several neurocognitons, in which agneurons of various types are located, connected with each other by initial contracts. Figure 11 shows the internal multi-actor cognitive architecture of the event agneuron, built at the stage of the embryonic development of an intelligent agent. In both cases, it can be seen that the formed multi-agent cognitive architectures contain a small number of agents between which a minimum number of connections are established.

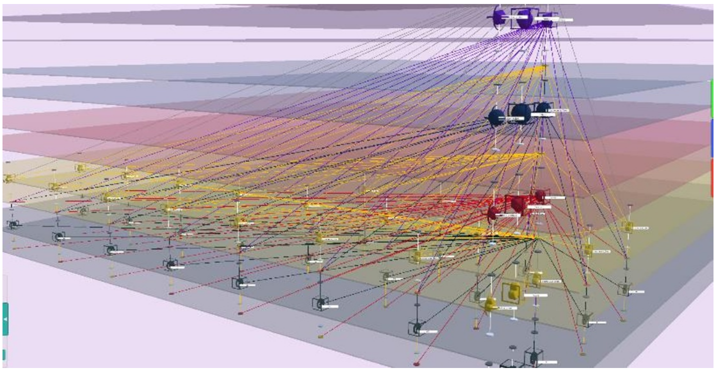

Fig. 11. "Postembryonic" phenotype of event agneuron

After the "birth" (placement in the simulation environment) of an intelligent agent, its "life" begins, the main goal of which is to maximize the target function of the energy that an intelligent agent needs to maintain its life. As a result of the transition to states associated with low energy values, the minimal multi-agent neurocognitive architecture of an intelligent agent (Figure 12), using the simulation model software options, synthesizes behavior aimed at interacting with users (operators) of the system in order to receive rewards from them in the form portions of energy. In the process of synthesis and implementation of such behavior, interaction with users based on sending messages to users and receiving messages and portions of energy from them, the states of the "agneuron-environment" systems, the "intelligent agent-environment" system arise, which are recognized by the antecedent parts of the production rules of actor genomes and agneurons as signs of events that require the launch of local genetic programs for element modification at different levels of the multi-agent neurocognitive architecture.

As a result of the launch of these decentralized phylogenetic processes distributed over the multi-agent neurocognitive architecture, the corresponding modifications are performed. The control cognitive architecture grows and develops, providing an intelligent agent with the ability to perform the target functionality by adapting its behavior to environmental conditions.

Figure 12 shows the visualization of the result of executing such phylogenetically determined multi-agent growth algorithms.

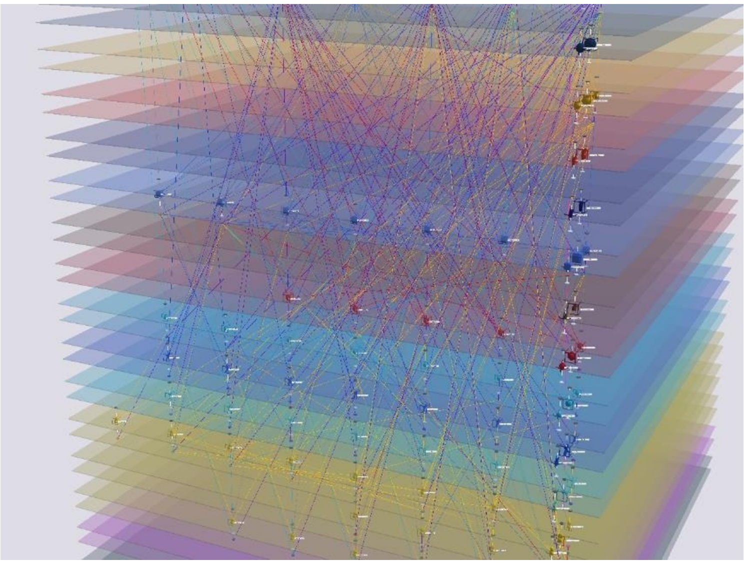

Fig. 12. The phenotype of an intelligent agent after ontophylogenetic training

Interestingly, from the point of view of external observers, all these changes are perceived as ontologically determined, since an intelligent agent begins to significantly change its behavior in the course of life. However, this process is actually dual, since at the level of the multi-agent neurocognitive architecture itself, it is completely phylogenetic.

In Figure 13, we see new agneurons, which in the course of this process were replenished with various neurocognitons of the multi-agent neurocognitive architecture. Within these agneurons, based on genetic information, their internal multi-actor cognitive architectures were also formed (Figure 13).

Both between the actors and between the agneurons, new contractual ties were formed. All this together has significantly transformed the multi-agent neurocognitive architecture, which, accordingly, will subsequently lead to a significant change in the behavior of an intelligent agent aimed at adapting to environmental conditions.

All these changes were the result of simulation modeling of the situationally determined expression of genes contained in the genomes of actors, agneurons, and an intelligent agent, which together form its genotype. Among these conditions, changes in the states of the "agneuron-environment", "intelligent agent-environment" systems, controlled by messages and rewards in the form of portions of energy received by the intelligent agent from users, were taken into account.

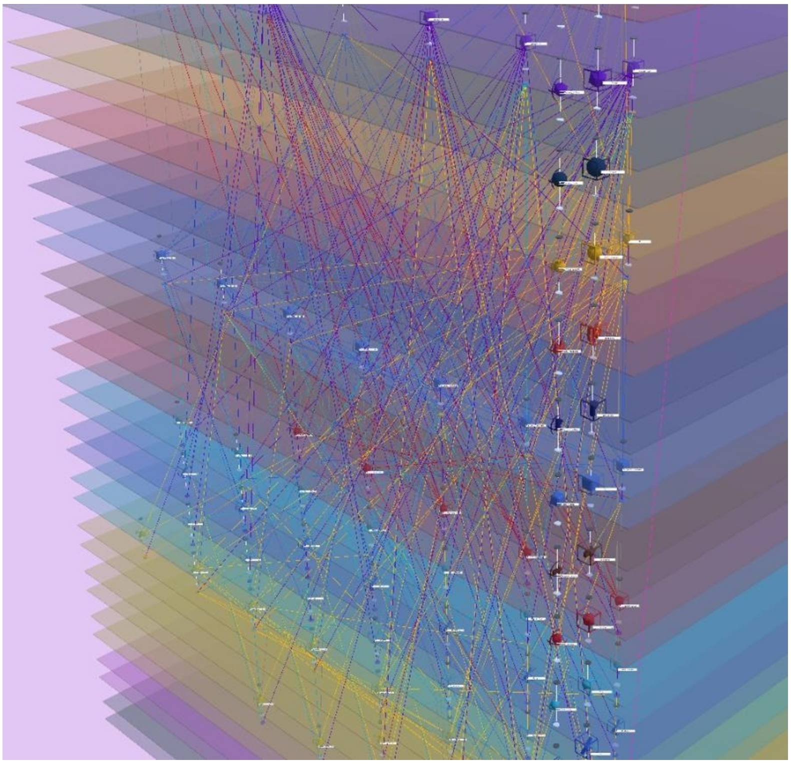

Fig. 13. Phenotype of event agneuron after ontophylogenetic training

Considering that such conditions occur periodically throughout the life of an intelligent agent, the accompanying processes of expression of genes contained at different levels of the intelligent agent genotype also occur constantly, which leads to an adaptive modification of the multi-agent neurocognitive architecture based on permanent ontophylogenetic learning.

5 Discussion

In general, if we move to the level of considering intelligent agents as independent individuals in the structure of populations representing the general configuration of the apparatus for finding solutions, even more questions arise. Should an agent have a mixed ontophylogenetic cycle, when the processes of ontological and genetic learning can take place synchronously and alternately during the entire time of the search for a solution (lifetime), the time of functioning of an intelligent agent? Should intelligent agents have periods of basic physical growth (by analogy with the intrauterine development of a child), "childhood" (socialization, during which the child is not required to solve tasks of assignment), puberty (the period following which the individual gets the opportunity to participate in multigenerational cycle of the genetic algorithm, "allowed" to exchange genes with other individuals)? Who should make the decision that the time has come to create a new generation - the initiator of the initial task, or the intelligent agent itself? Or should it be done by some consensus by the intelligent agents themselves, who should exchange genes? Should generations completely replace each other, or is it possible, in the process of solving the target problem, for the coexistence of agents of different generations and the possibility of crossing them with each other? What should be the target functions of intelligent agents in this case? Is it possible in this case to raise the question of the reproduction of intelligent agents as a means of adapting to the configuration of the space for solving the problem? Should reproduction then be bisexual? Multiploid?

In general, the abundance and depth of these questions promise genetic algorithms a long intensive future development, the prologue to which should be the creation of the first operating multi-agent systems of general artificial intelligence.

In our opinion, the strategy of bidirectional ontophylogenetic learning of intelligent agents must be implemented and thoroughly investigated theoretically and experimentally. The fact that in natural intelligent multicellular systems such a method was not implemented in the course of evolution, we associate not with the low efficiency of phenotypes formed in the "old" environmental conditions when they are used in the "new" environmental conditions, but rather with the physical limitations of ontological transformation. formed knowledge into the genomes and genotypes of multicellular organisms. Indeed, for this it would be necessary to evolutionarily synthesize in a series of millions of generations the mechanism of reverse coding of the "increment" of the phenotype into the "increment" of the genotype, which, obviously, is impossible in a natural biological system, since for this the mechanism of changing the entire genotype during life had to be implemented individuals.

At the same time, in an artificial system, in particular, in the ontophylogenetic system for teaching multi-agent neurocognitive architectures that we are developing, the implementation of such a mechanism is quite possible, since it does not encounter either physical or biological limitations. The procedure of reverse coding of the "increment" of the phenotype into the "increment" of the genotype can be implemented, since the formats of knowledge representation in the phenotype and genotype in our system are practically the same - in both cases these are production rules in the knowledge bases of software agents.

An important consequence of the implementation of the reverse coding procedure for the "increment" of phenotypes into the "increment" of the genotype will be the process of dynamic change in the structure and size of almost all genomes in the genotype of an intelligent agent. Genomes will increase due to "increment", which, of course, in a natural biological system would lead to numerous failures in the diploid synthesis of the genotype of a new organism. As for the genotype of the artificial intelligent agent that we are developing, then, in principle, by introducing additional tags and rules for the compatibility of different parts of the genomes, when implementing genetic algorithms, it is possible to ensure that individuals with "old" and "new" genomes effectively interbreed, giving offspring, having mixed hereditary traits that govern the "old" parts of the genomes, and hereditary traits that govern the "new" part of the genome for those traits for which there were simply no genes in the "old" genome. The simplest strategy here would be to package new genes, when back-coded, into new classified chromosomes, which would participate in the exchange of genetic material only if the crossing partner also has a chromosome belonging to the same class in the chromosome set, and otherwise case, they would simply be inherited by a new individual without changes.

Thus, with the introduction of such methods, there will be no need to eliminate successful intelligent agents when changing individuals in the population. In addition, such agents will be able to participate in the further phylogenetic development of the system using algorithms for mixed crossing of genotypes with different structures and sizes.

Such promising possibilities are based on a significant property of the artificial evolution of intelligent agents, which consists in the fact that in the process of correlation of the phenotype and genotype of an artificial organism, in contrast to a similar process applied to natural organisms, one can build an exact comparison of gene ensembles and their expression algorithms with the resulting phenotypic traits.

This property, together with the mechanisms for its provision, such as, for example, actor and neural factories, make it possible to implement a mixed ontophylogenetic cycle during the life of an intelligent agent, when the processes of ontological and genetic learning can take place synchronously and alternately during the entire time of the search for a solution, time functioning of an intelligent agent. As part of such a cycle, opportunities arise for external control over periods of basic physical growth and socialization, during which the intellectual agent (as a developing child) is not required to solve assignment tasks, the time of direct use of the intelligent agent to solve the tasks of the intended purpose, and the period of "puberty", when an intelligent agent gets the opportunity to participate in a multigenerational cycle of a genetic algorithm, it is “allowed” to exchange genes with other individuals). If we condition the decision-making on the transition of an intelligent agent from one of the above phases of maturity to another by the conditions for achieving a certain level of performance efficiency by its control multi-agent neurocognitive architecture, then it is possible to synthesize a new type of multi-stage genetic algorithm and a new ontophylogenetic learning method, which is one of the goals of our further research.

In this regard, the question of who should decide that the time has come to create a new individual, or a new generation of individuals, as well as a related question - with whom from the population to interbreed (exchange genes) is actualized? In evolutionary natural selection, both decisions are made by the individuals themselves, and, as a rule, on the basis of consensus, and the criteria for such a choice are far from always obvious. Theoretically, it is possible to imagine a situation where intelligent agents evaluate not only their capabilities for solving the target problem, but also the capabilities of other agents for solving this problem, as well as the possibilities of jointly solving this problem, and also the possibilities of solving it by future offspring, as well as and – the possibility of solving it jointly with future offspring. Taking into account the fact that the software agent of general artificial intelligence will be able to perform reasoning in order to solve a universal range of problems, reasoning about the future cooperative solution of the target problem using the collective interaction of related intelligent agents and descendants is, in principle, acceptable and constructive, which in general also opens prospects for the synthesis of a completely new method for the formation of phenotypes of new individuals with multigenerational ontophylogenetic optimization.

In this case, one can raise the question of the reproduction of intelligent agents as a means of adapting to the configuration of the problem solution space. Intelligent agents, having stated the low efficiency of attempts to solve the target problem on their own, can choose the tactics of creating alliances with other intelligent agents, including future ones, in order to create which it is necessary to organize matrimonial processes in the community of the most effective intelligent agents.

In this regard, the question of the ploidy of the genetic algorithm is actualized. It is obvious that the evolutionary division of the sexes is in many respects precisely determined by the need for social registration of the balance of calculations between synchronous agents of different generations. In this sense, differentiation in the process of evolution into only two sexes and two corresponding biological and social cycles may also have occurred due to the action of physical and biological limitations. Theoretically, based on the assessment of the effectiveness of a multigenerational ontophylogenetic algorithm in connection with the minimum amount of social costs in the collective organization of matrimonial behavior based on the differentiation of social roles and the support of maximum genetic diversity and variability of genotypes, it can be assumed that an increase in ploidy in proportion to an increase in the number of differentiated social roles could lead to an overall increase in efficiency.

When implementing multiploid genetic algorithms for the genotypes of such intelligent agents, one could rely on the concept of the presence of a large number of sexes, each of which would be distinguished on the basis of the differentiating unity of genetic and phenotypic traits, which provides the target individual with a certain type of matrimonial behavior and a certain role in solving the target problem. That is, it can be assumed that in the simulation model for the synthesis of the desired phenotype, several individuals can simultaneously cross, creating a polyploid genotype of this phenotype, based on information about what functional and social properties of behavior would need to be combined in the behavior of the target agent based on exchange of the respective genetic material of the parents.

6 Results

In the course of the study, a complex genome of an intelligent agent was developed, the features of a multichromosome genetic algorithm for organizing calculations in the paradigm of multigenerational optimization of multiagent neurocognitive architectures were established and substantiated.

It is shown that as a result of the application of such algorithms, the training of intelligent agents can be built on the basis of ontophylogenetic models, which combine the principles of intergenerational modification of the genomes of individuals and their development during the "life" (functioning) of these individuals.

It is shown that multigenerational optimization of the multi-agent neurocognitive architecture of intelligent agents can contribute to the achievement of adaptive resistance to the operating conditions of a general artificial intelligence agent, provide the synthesis of its suboptimal structural and functional scheme, accelerate learning and algorithms for finding solutions to a universal range of problems solved by this agent in its ecological niche.

The main principles of the application of ontophylogenetic methods and algorithms to achieve the ability to regulate the balance of the optimal ratio of the computational load necessary to find solutions to such problems between individuals in population generations based on a "natural" analogy are determined.

Experiments on the ontophylogenetic synthesis of phenotypes of general artificial intelligence agents based on multi-agent neurocognitive architectures based on the data of their complex genotype were carried out.

The basic principles of a multichromosomal genetic algorithm for crossing intelligent agents based on multi-agent neurocognitive architectures have been developed, taking into account structural and functional features and the specifics of using general intelligence agents to solve a universal range of problems.

7 Conclusion

"Natural" analogy, in which the phylogenetic part of development and learning is based on the processes occurring in the minimum structural and functional elements of the body - cells, the ontological part manifests itself at the level of macroscopic system-wide processes, and coordination between these two complexes of processes occurs on the basis of epigenetic feedbacks, creates the prerequisites for simulation modeling of all groups of factors operating in populations of "natural" intellectual systems - biological, environmental, social. Perhaps, the term “ontoepisociophylogenetic” would be suitable for designating such learning, indicating the balance of the computational load in the population of agents of general artificial intelligence under the conditions of simulation of their full life cycle, including such new and so far unusual phases for the field of evolutionary modeling, such as embryogenesis, postembryonic development , puberty (as achievement of the design level of functionality), matrimonial cycle, management of the social organization of computing.

The change of generations and genes, the need to achieve functional and "sexual" maturity are associated with the variability and complexity of the environment for the functioning (habitat) of natural intelligent agents. Multigenerational optimization is designed to ensure population adaptation to rapidly changing environmental conditions by updating gene sets based on those most adapted to current conditions. In a situation where, in the process of ontophylogenetic development, the inherently genetic processes of growth and division of cells that form various tissues create a material basis for situationally determined ontological learning based on changes in the composition and connectivity of the cognitive architecture of the brain, learning takes a certain, rather long time, and, most importantly, it faces natural limitations associated with cell aging and the accumulation of failures in genetic programs. Therefore, updating generations with the exchange of genes and restarting the cycle of individual development of agents solves the problem of compensating for the accumulation of errors and adapting the ontophylogenetic learning mechanism to the actual conditions of functioning of intelligent agents.

The specifics of the intended purpose of agents of general artificial intelligence is that, unlike systems of "weak" artificial intelligence, the design requirements, most likely, do not include specific tasks that such agents should be able to solve. Accordingly, to solve the problem of ontophylogenetic synthesis of an agent of general artificial intelligence, only a non-specialized function of a general type, focused on solving a universal range of problems in the ecological niche of such an agent, is well suited as an objective function. Constructive, in this case, is an approach in which we consider the goal of population evolution to be the synthesis of such individuals that succeed in the simulation model of natural selection. From a functional point of view, this means that such individuals solve some necessary universal range of tasks in their ecological niche at an acceptable level. In turn, this result, by analogy with populations of natural intelligent agents, means that if the configuration space of the ecological niche of an agent of general artificial intelligence coincides with the configuration space of tasks of the target functional (the spectrum of target problems), then the presence of such successful agents guarantees us the solution of any tasks. in this space at a high level in an acceptable time. Accordingly, by controlling the configuration of space, by simulating the ontophylogenetic learning of a population, it is also possible to control the development of agents of general artificial intelligence in order to achieve a given target functionality.

It should be noted that the division into ontological and phylogenetic parts in such a system can only be done in relation to the level of consideration. If in a multi-agent neurocognitive architecture all learning processes are associated only with the growth and development of its components (agneurons, actors, knowledge, contracts), and all these components develop only on a phylogenetic basis (if we consider epigenetically determined gene expression as a phylogenetic process), then it turns out that learning, which at the level of an external observer is perceived as ontological, at the level of these components themselves is phylogenetic.

Another approach to the differentiation of the two ways could be that in the ontogeny of an intelligent agent, the periods of “embryonic development” (the basic neurocognitive architecture is synthesized) and “life” (the agent begins to perform the target functionality) would be explicitly distinguished, and all knowledge, obtained at the first stage (immediately after the initiation of the intelligent agent, its "birth"), would be declared phylogenetic, and at the second - ontological.

Multi-generational optimization of general intelligence agents is an exciting new world that requires several more decades of theoretical work and the development of experimental research models to explore.

8 Acknowledgements

This research was supported by the Russian Science Foundation grant No. 22-19-00787.

References

1. M.I. Anchekov, Proceedings of the Kabardino-Balkarian Scientific Center of the Russian Academy of Sciences **2-2(46),** 56-61 (2012)
2. M.I. Anchekov, et.al, Proceedings of the Kabardino-Balkarian Scientific Center of the Russian Academy of Sciences **5(109),** 25-37 (2022)
3. M.I. Anchekov, et.al, Proceedings of the Kabardino-Balkarian Scientific Center of the Russian Academy of Sciences **5(109),** 19-24 (2022)
4. F. Bellas, et.al, IEEE Trans. Auton. Mental Dev. **2(4),** 340–354 (2010) https://doi.org/10.1109/TAMD.2010.2086453
5. S. Budaev, et.al, Biologically Inspired Cognitive Architectures **25,** 51–57 (2018) https://doi.org/10.1016/j.bica.2018.07.009
6. R. Doursat, Organic Computing, pp. 167-200 (2008b)
7. A. Fedor, et.al, Front. Psychol. **8** (2017) https://doi.org/10.3389/fpsyg.2017.00427
8. Awni Hannun, The Role of Evolution in Machine Intelligence (2021)
9. Information on https://en.wikipedia.org/wiki/Neuroevolution
10. Z.V. Nagoev, Intelligence, or thinking in living and artificial systems (Nalchik, KBNTs RAS Publishing House, 2013)
11. Z.V. Nagoev, Biologically Inspired Cognitive Architectures 2012, Proceedings of the third annual meeting of the BICA Society, in Advances in Intelligent Systems and Computing series, pp. 247-248 (2012)
12. Z.V. Nagoev, Proceedings of the Kabardino-Balkarian Scientific Center of the Russian Academy of Sciences **4(54)** (2013)
13. Z.V. Nagoev, O.V. Nagoeva, Symbol substantiation and multi-agent neurocognitive models of natural language semantics (Nalchik, KBNTs RAS Publishing House, 2022)
14. Z.V. Nagoev, O.V. Nagoeva, News of the Kabardino-Balkarian Scientific Center of the Russian Academy of Sciences **3(83),** 11-20 (2018)
15. Z.V. Nagoev, et.al, Cognitive Systems Research **66,** 82-88 (2021)
16. Lee Spector, Kilian Stoffel, Ontogenetic Programming (1998)
17. J. Togelius, et.al, Fachbeitrag **03** (2009)
18. J. Werfel, R. Nagpal, IEEE Intelligent Systems **21(2),** 20-28 (2006)