What is natural way to artificial intelligence? [1]

Vladimir G. Red'ko
M.V. Keldysh Institute for Applied Mathematics, Moscow, Russia

E-mail: redko@keldysh.ru
URL: http://www.keldysh.ru/BioCyber/

Abstract. *The chapter argues that the investigations of evolutionary processes that result in human intelligence by means of mathematical/computer models can be serious scientific base of AI researches. The "intelligent inventions" of biological evolution (unconditional reflex, habituation, conditional reflex…) to be modeled, conceptual background theories (the metasystem transition theory by V.F.Turchin and the theory of functional systems by P.K. Anokhin) and modern approaches (Artificial Life, Simulation of Adaptive Behavior) to such modeling are outlined. Two concrete computer models "Model of Evolutionary Emergence of Purposeful Adaptive Behavior" and "Model of Evolution of Web Agents" are described. The first model is a pure scientific investigation; the second model is a step to practical applications. Finally, a possible way from these simple models to implementation of high level intelligence is outlined.*

Key words: natural and artificial intelligence, evolutionary roots of natural intelligence, modeling of "intelligent inventions" of biological evolution, a way to high level AI.

1. Introduction

Artificial intelligence (AI) is an area of applied researches. Experience demonstrates that an area of applied researches is successful, when there is a powerful scientific base for the area. For example, solid state physics was the scientific base for microelectronics in the second part of 20-th century. It should be noted that solid state physics is very interesting for physicists from scientific point of view. Therefore, physicists made a lot in scientific basis of microelectronics, independently of possible applications of their results. And results of microelectronics are colossal. Microelectronics is everywhere now.

What could be a scientific base of AI (analogously to the scientific base of microelectronics)? We can consider this problem in the following manner. Natural human intelligence was emerged through biological evolution. It is very interesting from scientific point of view to study evolutionary processes that resulted in human intelligence, to study cognitive evolution, evolution of cognitive animal abilities. Moreover, investigations of cognitive evolution are very important from epistemological point of view: such investigations could clarify the very profound epistemological problem: why is human intelligence, human thinking, human logic applicable to cognition of nature? Therefore, we can conclude, that investigation of cognitive evolution can be the natural scientific base of AI developments.

What could be a subject of investigations of cognitive evolution? What could be a relation between academic investigations of cognitive evolution and applied AI researches? In my opinion, it is natural 1) to develop mathematical/computer models of "intelligent inventions" of biological evolution (such as unconditional reflex, habituation, conditional reflex and so on), 2) to represent by means of such

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models a general picture of cognitive evolution, and 3) to use these models as a scientific background for AI researches. The goal of this chapter is to propose and discuss steps to such researches.

The structure of the chapter is as follows. The section 2 discusses an epistemological problem that can stimulate investigations of cognitive evolution. The section 3 outlines the subject of these investigations and some conceptual approaches to the investigations. The section 4 describes two concrete and rather simple models: "Model of Evolutionary Emergence of Purposeful Adaptive Behavior" and "Model of Evolution of Web Agents". The section 5 outlines a possible way from these simple models to implementation of higher cognitive abilities.

2. The epistemological problem

There is a very interesting and profound epistemological problem: why is *human* intelligence applicable to cognition of *nature*?

To illustrate the problems, let's consider physics, the most fundamental natural science. The powerfulness of physics is due to extensive and effective use of mathematics. However, why is mathematics applicable to physics? Indeed, a mathematician creates his theories, using his intelligence, quite independently from real physical world. The mathematician can work in a silence of his cabinet, resting on a sofa, in an isolated prison cell. Why are his results applicable to real nature?

Are we able to approach to solution of these questions? In my opinion, yes. We can analyze evolutionary roots of human intelligence and try to investigate why and how did high level intelligent cognitive abilities evolutionary emerge. In other words, we can follow evolutionary roots of animal and human cognitive abilities and represent a general picture of evolutionary emergence of human thinking, human intelligence. We can analyze, why and how did animal and human cognitive features emerge, how do these cognitive features operate, why are they applicable to cognition of nature.

Can we really proceed in this way? Can we find evolutionary roots of human intelligence in animal cognition properties? Yes, we can. Let's consider the elementary logic rule that is used by a mathematician in deductive inferences, modus ponens: "if A is present and B is a consequence of A, then B is present", or $\{A, A \rightarrow B\} \Rightarrow B$.

Now let's go from the mathematician to a Pavlovian dog (Pavlov, 1927). The dog is subjected to the experiment of classical conditioning. A neutral conditioned stimulus (CS), a sound is followed by a biologically significant unconditioned stimulus (US), a food. The unconditioned stimulus arouses salivation. After a number of presentations of the pair (CS, US), the causal relation CS -> US is stored in dog's memory. Using this relation at a new presentation of the CS, the dog is able to do elementary "inference": {CS , CS -> US } => US. Then expecting the US, the dog salivates.

Of course, the application of modus ponens rule (purely deductive) by the mathematician and the inductive "inference" of the dog are obviously different. However, can we think about evolutionary roots of logical rules used in mathematics? Yes, we certainly can. The logical conclusion of the mathematician and the "inductive inference" of the dog are qualitatively similar.

Moreover, we can go further. We can imagine that there is a semantic network in the dog's memory. This network is a set of notions and links between notions. For example, we can imagine that the dog has notions "food", "danger", "dog of the opposite sex " – these notions correspond to main animal needs: energy, safety and reproduction. Further, the notion "food" can have semantic links to notions "meat", "bread" and so on. We can also imagine that a semantic link between a CS and a US is generated in dog's memory at classical conditioning. For example, if the CS is a sound and the US is meat, then the semantic link between the CS and the US can be illustrated by Fig. 1.

sound $\xrightarrow{\text{follows}}$ **meat**

Fig. 1. Illustration of the semantic link between the conditioned and unconditioned stimuli: the meat follows the sound.

We can further imagine generation and development of different semantic networks during dog's life. These networks reflect dog's experience and stored in dog's memory. To some extent, these semantic networks are similar to semantic networks that are studied in AI researches (see e.g. Goertzel, 2001).

So, we can think about evolutionary roots of inference rules and logical conclusions.

Additionally, I would like to note here an interesting analogy between conditioned reflex and the Hume's consideration of notion of causality.

In 1748 David Hume wrote "Philosophical Essays Concerning Human Understanding" (Hume, 1748), where he called in question the notion of causality, one of the main scientific concept. Briefly, the Hume's argumentation is as follows.

If we observe that some event A is many times followed by another one B, we usually conclude that the first event A is the cause of the second event B. For example, if we see that some moving billiard ball hits a second resting ball (event A) and the second ball begins to move (event B), and if we observe a series of such event pairs (A -> B), then we conclude that the hit of the first ball is the cause of the movement of the second ball.

What is an origin of this conclusion?

According to Hume, we have not a solid reason for this. If we analyze thoroughly the issue, we can establish that only custom and habit as well as some "internal feeling" force us to establish the relation between causes and effects. See (Red'ko, 2000) for some details of Hume's argumentation.

A dog in experiments of classical conditioning establishes a relation between conditioned stimulus (CS) and unconditioned stimulus (US). We can say that after repetition of a number of events CS --> US, some "internal feeling" forces the dog to establish the relation between "cause" (CS) and "effect" (US), in very similar manner as a human does this in the Hume's "thinking experiments".

Therefore, we can follow (at least intuitively and in very general terms) the relation between classical conditioning and prediction between causes and effects. We can try to answer to Hume's question "Why can we deduce that some event is the cause of another event?", analyzing evolutionary roots of classical conditioning and investigating, what neural network of a dog (or a more simple animal) can produce "internal feeling" that forces the dog to establish the relation CS --> US.

Concluding the section, we can say, that there is the important epistemological problem: why is human intelligence applicable to cognition of nature? The epistemological problem is important – it concerns the foundation of the whole science. Consequently, it is important to investigate this problem in maximally full extent. We can try to solve the problem analyzing evolutionary roots of human intelligence. We can analyze how did human logic rules and other constituents of human thinking origin through biological evolution. Going further, we can design mathematical/computer models of "intelligent inventions" of biological evolution and try to create a theory of evolutionary origin of human intelligence.

What could be a subject of this theory? What "intelligent inventions" of biological evolution could be modeled? What models have been already created? What conceptual theories could be used in these investigations? These questions are discussed in the next section.

3. Approaches to the theory of evolutionary origin of human intelligence

In order to do the first steps towards a theory of evolutionary origin of human intelligence, it is natural to represent a picture of evolution of animal cognitive abilities and some conceptual schemes, which could help us to model the process of evolution of "intelligent" properties of animals. This section tries to represent such picture of cognitive evolution and to describe such conceptual schemes.

3.1. "Intelligent inventions" of biological evolution

We begin here from the very beginning – from the simplest forms of live – and try to extract levels of "intelligent inventions" of biological evolution. We mention examples of "inventions" and corresponding mathematical/computer models, which have been already developed.

First level. An organism perceives different states of external environment; the information about these states is memorized in the organism genome and is inhered. The organism adaptively uses the information about these states by changing its behavior in accordance with changes of the environment states.

An example of this level is the *regulation of enzyme synthesis* in bacteria in accordance with the classical scheme by F. Jacob and J. Monod (1961). This scheme of regulation can be outlined as follows. Bacterium *E. Coli* uses glucose as its main nourishment. However, if glucose is absent, but another substrate, lactose is present in environment, *E. Coli* turns on the synthesis of special enzymes, which transform lactose into the usual nourishment, glucose. When bacterium returns into glucose-rich environment, the synthesis of transforming enzymes is turned off. This scheme of regulation can be considered as the unconditional reflex at molecular-genetic level. It can also be considered as a scheme of primordial control system.

The mathematical model of such scheme of regulation, "Adaptive syser" was created and analyzed by V.G. Red'ko (1990). The model represents a possible scheme of origin of primeval control system at prebiological level.

Second level. An organism individually stores the information about situations in external environment in its short-term memory. This memorizing ensures the acquired adaptation of the organism to events in the environment.

An example of this level is the *habituation* of infusoria, demonstrated by W. Kinastowski (1963). If an infusorium is subjected many times to a neutral stimulus, e.g. drop of water, its reaction (twitching) on the stimulus is initially large, but in further course of the experiment, the reaction is decreased. This form of adaptation is of short-term type. According to experiments of W. Kinastowski, the habituation of infusoria is formed during 10-30 minutes, it is maintained during 1-3 hours.

Tsetlin's automata are well-developed mathematical models that correspond approximately to "intelligence level" of habituation (Tsetlin, 1973). Tsetlin's automata illustrate simple acquired properties of biological organisms and simple adaptive behavior in changing external environment. Last decade the models of habituation are developed in the field of "Adaptive Behavior" (e.g. Staddon, 1993).

Third level. An organism individually stores the causal relations between the events in external environment. The causal relations are stored in long-term memory.

An example of this level is *classical conditioning*. In well-known experiments of I.P. Pavlov (1927) on a dog, a neutral conditioned stimulus, CS was followed by a biologically significant unconditioned stimulus, US. The unconditioned stimulus aroused certain unconditioned response. After a number of presentations of the pair "CS --> US", the CS alone became able to arouse the same (conditioned) response.

The classical conditioning has several non-trivial particularities. There are three stages of learning procedure in classical conditioning: pre-generalization, generalization, and specialization (Kotlyar & Shulgovsky, 1979). During the pre-generalization, the conditioned response is still absent, but there is the increase of electrical activity in different areas of an animal brain. During the generalization, both the CS and other (differential) stimuli, which are similar to the CS, arouse the conditioned response. The generalization is followed by specialization, at which the response to differential stimuli is gradually vanished whereas the response to the CS is retained.

The causal relation between CS and US is stored in the long-term memory: a conditional reflex is conserved during several weeks for low-level vertebrates and up to several years (and may be during the whole life) for high-level animals. The characteristic feature of classical conditioning is the spontaneous recovery: the renewal of a conditioned response, which takes place several hours after extinguishing of a conditional reflex (Voronin, 1977). The biological meaning of classical conditioning is foreseeing of future events in environment and adaptive use of this foreseeing (Anokhin, 1974, 1979).

There are a number of mathematical and cybernetic models of conditional reflex, created and investigated by A.A. Lyapunov (1958), S. Grossberg (1974), A. Barto & R. Sutton (1982), A.H.Klopf et al (1993) and others. However, in my opinion, some significant aspects of classical conditioning have not been mathematically described yet (the similar viewpoint was expressed by C. Balkenius and J. Moren (1998)). This concerns mainly the feature of the spontaneous recovery, the role of a motivation in conditional learning, and the biological meaning of the classical conditioning.

There are several levels of "intelligent inventions" between classical conditioning and human intelligence. We only mention some of them here.

Instrumental conditioning is similar to classical conditioning, but it is more complex: an animal has to discover adequate new conditioned response (that is not known to it in advance), in order to obtain a reinforcement after a presentation of a conditional stimulus.

Chains of conditioning is a sequence of conditioned responses that is formed on the base of old conditioned relations, which have been already stored in animal memory.

High-level animals use the non-trivial *models of external environment* in their adaptive behavior. Certainly, some forms of "behavioral logic" are used in such modeling in order to predict future situations and to reach a goal. Examples of such "intelligent" behavior are well-known experiments of W. Köhler (1925) on apes. Apes were able to use several instruments (sticks, boxes) on order to get over several difficulties and solve a complex task of reaching food. Obviously, apes use certain models and certain logic during solving these tasks.

The *final level*, we consider, is *human logic*. The mathematical theories of our logic are well developed. There is the propositional calculus, there is the predicate calculus (Kleene, 1967), and there are theories of mathematical inference (Gentzen, 1935,1936). Theories of inductive and fuzzy logic were intensively developed in last decades (Angluin, Smith, 1983, Zadeh, 1973, Zadeh et al, 1996).

Thus, it is possible to extract the several key "intelligent inventions" and consider the sequence of achievements of biological evolution (Fig.2). The abilities to cognize the natural phenomena is gradually increased in this sequence.

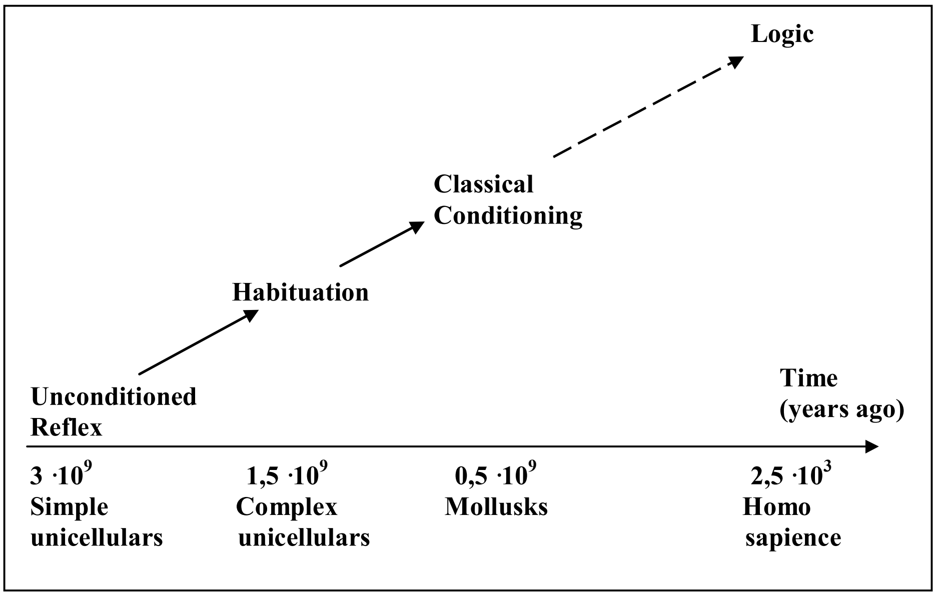

Fig.2. “Intelligent inventions” of biological evolution. "Authors of inventions and priorities dates" are shown highly approximately.

Analysis of existing models of “intelligent inventions” demonstrates that we are very far from full-scale theory of evolution of cognition. The models developed can be considered only as first steps towards such a theory. These models have obviously fragmentary character; there are no models, which could describe the transition stages between the intelligent inventions of different evolutionary levels.

Thus, modeling of "intelligent inventions" of biological evolution is at initial stages of development. Therefore, it is reasonable to consider ideas and methodological schemes, which could help to model these "inventions". Below we will outline some of methodological approaches: the metasystem transition theory by V.F. Turchin (1977) and the theory of functional system by P.K. Anokhin (1974, 1979).

3.2. Methodological approaches

3.2.1. Metasystem transition theory by V.F. Turchin

In the book "The Phenomenon of Science. A Cybernetic Approach to Human Evolution", Turchin outlined the evolution of cybernetic properties of biological organisms and considered the evolution of scientific cognition as a continuation of biocybernetic evolution (Turchin, 1977). In order to interpret the increase of complexity of cybernetic systems during evolution, Turchin proposed the *metasystem transition theory*. This theory introduced a general cybernetic scheme of evolutionary transitions between different levels of biological organization.

Briefly, the metasystem transition theory can be outlined as follows (Fig.3). A transition from a lower level of system hierarchy to a next higher level is a symbiosis of a number of systems $\boldsymbol{S}_i$ of the lower level into the combined set $\Sigma_i \boldsymbol{S}_i$; the symbiosis is supplemented by emergence of the additional system $\boldsymbol{C}$, which controls the behavior of the combined set. This metasystem transition results in creation of the system $\boldsymbol{S'}$ of new level ($\boldsymbol{S'} = \boldsymbol{C} + \Sigma_i \boldsymbol{S}_i$). The system $\boldsymbol{S'}$ can be included as a subsystem into the next metasystem transition.

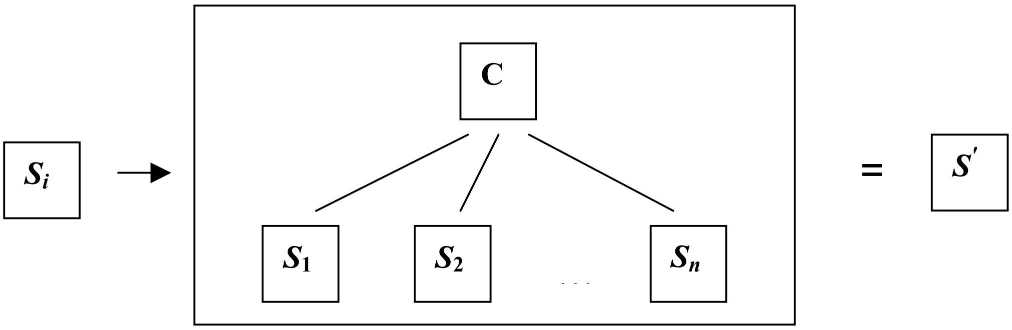

Fig. 3. Scheme of a metasystem transition. $\boldsymbol{S}_i$ are systems of the lower level, $\boldsymbol{C}$ is the control system, $\boldsymbol{S'}$ is the system of the new (higher) lever.

Turchin characterizes biological evolution by the following main metasystem transitions:

control of position = movement
control of movement = irritability (simple reflex)
control of irritability = (complex) reflex
control of reflex = associating (conditional reflex)
control of associating = human thinking
control of human thinking = culture

Turchin describes the metasystem transition as certain cybernetic analog of the physical phase transition. He pays special attention to quantitative accumulation of progressive traits in subsystems S_i just before a metasystem transition and to multiplication and developments of subsystems of the penultimate level of the hierarchy after the metasystem transition.

The metasystem transition theory provides us with the interpretation of general processes of evolutionary increase of complexity. The more intimate processes of intelligent adaptive behavior can be analyzed on the base of the theory of functional systems, which was proposed and developed in the 1930-1970s by Russian physiologists P.K. Anokhin (1974, 1979).

3.2.2. Theory of functional systems by P.K. Anokhin

Anokhin's *functional system* is a neurophysiological system that is aimed at achievement of an organism's vital needful result. The main mechanisms of the functional system operation are (Fig.4):

1) afferent synthesis,
2) decision making,
3) generation of an acceptor of an action result,
4) generation of the action (efferent synthesis),
5) the complex action,
6) an achievement of a result,
7) backward afferentation about parameters of the result, comparison of the result with its model that were generated in the acceptor of the action result.

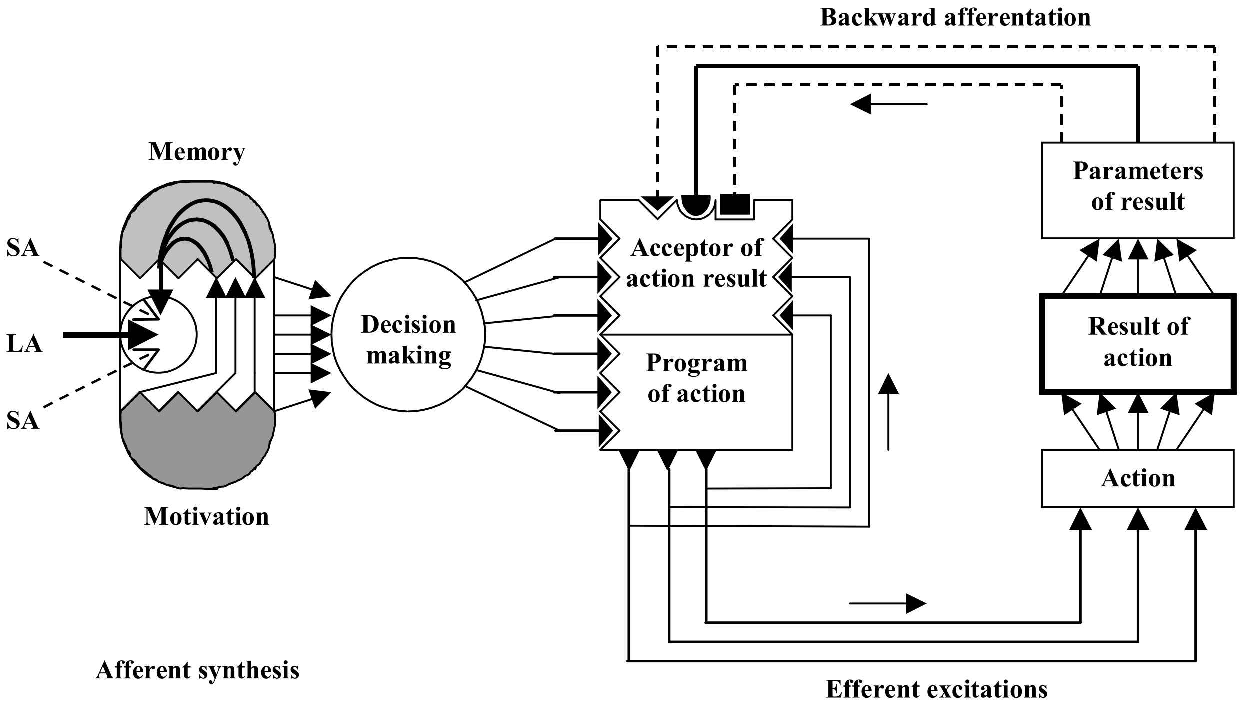

Fig. 4. General architecture of a functional system. LA is launching afferentation, SA is situational afferentation.

Operation of a functional system can be described as follows.
An *afferent synthesis* involves synthesis of neural excitations that are due to 1) dominating motivation, 2) situational afferentation, 3) launching afferentation, and 4) inherited and acquired memory.

The afferent synthesis is followed by *decision making*, which means a reduction of degree of freedom for an efferent synthesis and selection of a particular action in accordance with dominating animal need and other constituents of the afferent synthesis.

Next step of the operation is the generation of the *acceptor of the action result*. This step is the formation of a prognosis of the result. The prognosis includes forming of particular parameters of the foreseeing result.

The *efferent synthesis* is a preparation for the effectory action. The efferent synthesis implies generation of some neural excitations before generation of an action command.

All stages of result achievement are permanently estimated by means of *backward afferentation*. If parameters of an actual result are different from parameters of the acceptor of action result, then the action is interrupted and new afferent synthesis takes place. In this case, all operations of the functional system are repeated until the final needful result is achieved.

Thus, operation of the functional system has a cyclic (with backward afferent links) self-regulatory organization.

The most important particularity of Anokhin's theory is orientation of operation of any functional system to achievement of a *final needful result*.

The next particularity is *dynamism, temporality*. At each behavioral action, different neural and other regulatory structures of an organism are mobilized into a functional system.

In addition, an important concept of the functional system theory is *systemogenesis*. The essence of systemogenesis is that organism functional systems – needed for adaptive behavior of animals and men – are ripen at both pre-natal period and ontogenesis.

It should be underlined that the theory of functional systems was proposed and developed in order to interpret a number of neurophysiological data. The theory was formulated in rather general and intuitive terms. In my opinion, it provides us with important *conceptual* approach to understanding of brain operation. This theory could help us to understand neurophysiological aspects of prognosis, foreseeing, creation of casual relation between situations and generation of "semantic networks" (such as shown in Fig.1) in animal brains and minds.

3.3. Role of investigations of "Artificial Life" and "Simulation of Adaptive Behavior"

Let's return to the question of modeling of "intelligent inventions" of biological evolution. Fortunately, two interesting directions of investigations – "Artificial Life" and "Simulation of Adaptive Behavior" – appeared 12-15 years ago, which can helps us. We can use methods, concepts and approaches of these researches during creating and developing models of "intelligent inventions".

Artificial Life (Alife), as an area of investigations, took its form in the later 1980s (Langton, 1989, Langton et al, 1992). The main motivation of Alife is to model and understand the formal rules of life. As C.G. Langton said, "...the principle assumption made in Artificial Life is that the 'logical form' of an organism can be separated from its material basis of construction" [1]. Alife "organisms" are man-made, imaginary entities, living mainly in computer-program worlds. Evolution, ecology, and the emergence of new features of life-like creatures are under special attention of the Alife researches.

Simulation of Adaptive Behavior (Meyer & Wilson, 1990) is an area of investigations that is very close to Alife. However, it is more specialized – the main goal of this field of research is "designing animats, i.e., simulated animals or real robots whose rules of behavior are inspired by those of animals. The proximate goal of this approach is to discover architectures or working principles that allow an animal or a robot to exhibit an adaptive behavior and, thus, to survive or fulfill its mission even in a changing environment. The ultimate goal of this approach is to embed human intelligence within an evolutionary perspective and to seek how the highest cognitive abilities of man can be related to the simplest adaptive behaviors of animals" (Donnart & Meyer, 1996).

We can see that the ultimate goal of Simulation of Adaptive Behavior is very close to the task of creation of a theory of evolutionary origin of human intelligence as it was discussed above.

Thus, we have stated the problem of development of scientific base of AI researches and analyzed general approaches to corresponding investigations. Now it is time to make some concrete steps. To exemplify possible researches, we describe below two concrete computer models: “Alife Model of Evolutionary Emergence of Purposeful Adaptive Behavior” and “Model of Evolution of Web Agents”. These models have a number of common features and illustrate possible interrelations between purely academic investigations of cognitive evolution (first model) and applied researches directed to Internet AI (second model).

4. Two models

4.1. Alife model of evolutionary emergence of purposeful adaptive behavior[2]

The purpose of this model is to analyze the *role of motivations* for simple adaptive behavior. Note, that motivation is the important feature of the Anokhin' theory of functional system (the section 3.2.2). Namely, a dominating motivation – that corresponds to a current animal need – takes part in generating behavioral action.

4.1.1. Description of the model

The main assumptions of the model are as follows:

- There are agents (Alife organisms), which have two natural needs (the need of energy and the need of reproduction).
- The population of agents evolves in the simple environment, where patches of grass (agent's food) grow. The agents receive some information from their environment and perform some actions. Agents can move, eat grass, rest and mate with each other. Mating results in birth of new agents. An agent has an internal energy resource R; the resource is increased during eating. Performing an action, the agent spends its resource. When the resource of the agent goes to zero, the agent dies.
- Any need of an agent is characterized by a quantitative parameter (motivation parameter) that determines the motivation to reach a corresponding purpose. E.g., if energy resource of an agent is small, there is the motivation to find food and to replenish the energy resource by eating.
- The agent behavior is controlled by a neural network, which has special inputs from motivations. If there is a certain motivation, the agent can search for solution to satisfy the need according to the motivation. This type of behavior can be considered as *purposeful* (there is the purpose to satisfy the need).
- The population of agents evolves. The main mechanism of the evolution is the formation of genomes of new agents with the aid of crossovers and mutations. A genome of the agent codes the synaptic weights of the agent's neural network.

The environment in our model is a linear one-dimensional set of cells (Fig. 5). We assume that only a single agent can occupy any cell.

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[2] This model was created and developed together with Mikhail S. Burtsev and Roman V. Gusarev (Burtsev et al, 2001).

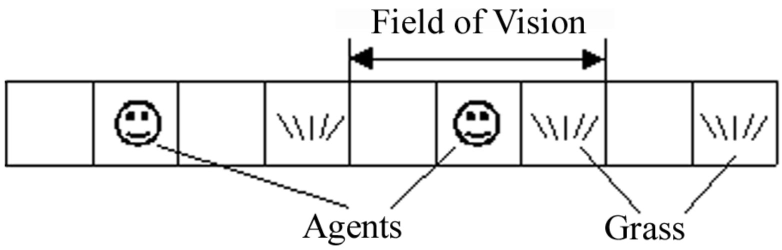

Fig. 5. Agents in the one-dimensional cellular environment.

The time is discrete. At any time iteration, each agent executes exactly one action. The set of possible actions of agents is the following: 1) resting; 2) moving to a neighboring cell (to the left or to the right); 3) jumping (over several cells into random direction); 4) eating; 5) mating.

The grass patches appear randomly and grow certain time at cells of the environment. The agents are "short-sighted". This means that any agent views the situation only in three cells: in its own cell and in two neighboring cells. We designate these three cells as "field of vision" of an agent (Fig. 5).

We introduce two quantitative parameters, corresponding to the agents needs:
1) Motivation to search the food M_E that corresponds to the need of energy;
2) Motivation to mating M_R that corresponds to the need of reproduction.

Motivations are defined as follows (Fig. 6):

$$M_E = \max\left\{\frac{R_0 - R}{R_0},\ 0\right\},\quad M_R = \min\left\{\frac{R}{R_1},\ 1\right\},$$

where R_0 is some "optimal" value of energy resource R, R_1 is the value of energy resource, which is the most appropriate for reproduction.

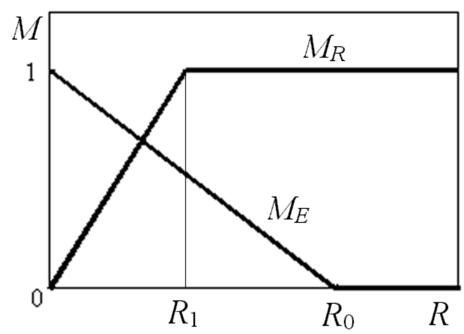

Fig. 6. Dependence of motivations M_E, and M_R on energy resource R of an agent.

The neural network of an agent controls its behavior. We suppose that the neural network includes one layer of neurons. The neurons receive signals from external and internal environment via sensory inputs. There are full interconnections between sensory inputs and neurons: each neuron is connected to any input. The outputs of neurons determine agent's actions. Each neuron corresponds to one action. Taking into account that actions "moving" and "mating" have two variants (an agent can move to the left or to the right and mate with left or right neighbor), we have 7 neurons. Each neuron has 9 sensory inputs. Since inputs and neurons have all possible synaptic interconnections, there are 9x7 = 63 synaptic weights in the neural network. The neurons have typical logistic activation function.

We assume that at the given moment of time the agent accomplishes the action, corresponding to that neuron, which has maximal output signal.

The scheme of the evolution is implemented in the following way. We assume that a genome of an agent codes synaptic weights of the agent's neural network. Each synaptic weight is represented by a real number and considered as a gene of the genome. When a new agent is being born, its genome is created in the following manner: 1) a uniform recombination of parent's genomes is formed, 2) this recombined genome is subjected to small mutations.

4.1.2. Results of computer simulations

To analyze the influence of motivations on behavior of agents, we performed two series of simulations. In the first series, the agents had motivations (the motivations were introduced as described above). In the second series, the agents had no motivations (the inputs from motivations were artificially suppressed by means of special choice of parameters R_0, R_1). In order to analyze the influence of food amount in the external environment on population behavior, the simulations in both series were performed for the several probabilities of grass appearance in cells.

Choosing certain parameters, which determine energy consumption at agent actions, we defined some reasonable agent physiology. We chose also some reasonable values of parameters R_0, R_1 and starting values of energy resource of agents in initial population.

All agents of the initial population had the same synaptic weights of neural networks. These weights determined some reasonable initial instincts of agents.

The first instinct was the instinct of food replenishment. This instinct was dedicated to execute two types of actions: 1) if an agent sees a grass in its own cell, it eats this grass; 2) if an agent sees a grass in a neighboring cell, it moves into this cell.

The second instinct was the instinct of reproduction. This instinct implies that if an agent sees another agent in one of the neighboring cells, it tries to mate with this neighbor.

In addition to these main instincts, the agents were provided with the instinct of "fear of tightness": if an agent sees two agents in the both neighboring cells, it jumps.

The synaptic weights from motivational inputs in the neural network were equal to zero for all agents in initial population. Therefore, motivations began to play role only in the course of evolution.

The main quantitative characteristics that we used in order to describe the quality of an evolutionary process was the total number of agents in population N. We obtained the dependencies $N(t)$ on time t for both series of experiments: for population of agents with motivations and for population of agents without motivations. We also analyzed evolutionary dynamics of agent actions and registered a statistics of the synaptic weights during a process of evolution.

Examples of the dependencies $N(t)$ are shown in Fig. 7. At small amount of food (Fig. 7a), both populations of agents (with and without motivations) die out – the amount of food is not enough to support consumption of energy needed for agent actions. At mean amount of food (Fig. 7b), the population of agents without motivations dies out, whereas the population of agents with motivations is able to find a “good” living strategy and survives. At large amount of food (Fig. 7c), both populations survive, however, the population with motivations finds better neural network control system, which ensures the larger final population.

Thus, neural network inputs from internal motivations provide an opportunity for the population to find better control system for agents in the course of evolutionary search.

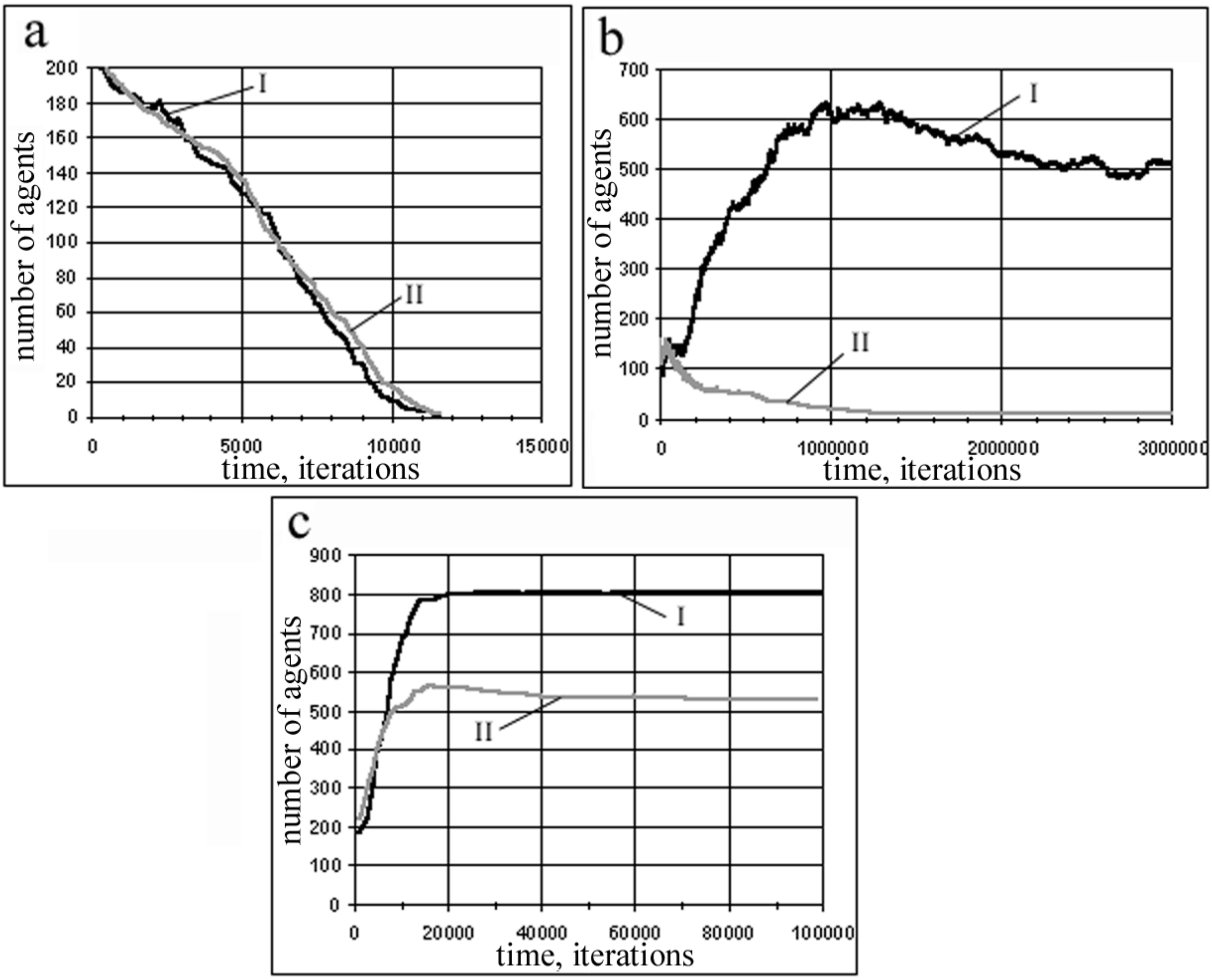

Fig. 7. Dependencies of number of agents in population with motivations (I) and without motivations (II) on time $N(t)$ for different probabilities of grass appearance, P_g: a) P_g = 1/2000, b) P_g = 1/200, c) P_g = 1/20.

4.1.3. Interpretation of results of simulation

We performed detailed analysis of agents’ actions evolution for population with and without motivations. Basing on this analysis, we interpreted behavioral control of agents.

The scheme of behavioral control of agent *without motivations* that was discovered by evolution is shown in Fig. 8. This scheme includes three rules, which are used by an agent during its life.

The first rule says that if the agent sees a grass patch, it seeks to eat this food. Namely, it eats food, if the food is in its own cell, or goes to grassy neighboring cell and eats food at the next moment of time.

The second rule says that if the agent sees a neighbor, it makes mating action, trying to give birth to an offspring.

These two rules are just instincts, which we forced to agents of an initial population. The evolution confirmed that they are useful and adaptive.

The third rule says that if the agent doesn't see anything in its field of vision, it decides to rest. This rule was discovered by evolution, and, of course, the rule has a certain adaptive value.

It is obvious that such agent behavior is determined by current state of the external environment only. These three rules can be considered as simple reflexes.

Fig. 8. Scheme of behavioral control of agents without motivations.

Let's consider the control system of an agent *with motivations*. The analysis of simulations demonstrates that the control scheme of an agent with motivations can be represented as a hierarchical system. Three rules described above constitute the lower level of the control system. The second level is due to motivations. This hierarchical control system works in the following manner (Fig. 9).

If the energy resource of an agent is low, the motivation to search food is large, and the motivation to mating is small, so the agent uses only two of mentioned rules, the first and the third – the mating is suppressed. If the energy resource of the agent is high, the motivation to mating is turned on, and so the agent seeks to mate – the second and the third rules govern mainly the agent behavior, however, sometimes the first rule works too.

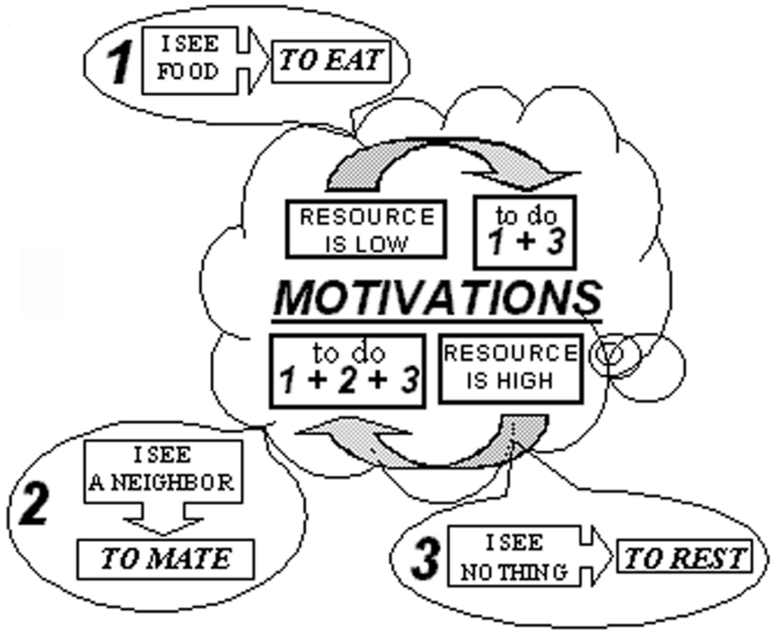

Fig. 9. Scheme of behavioral control of agents with motivations.

So, the transition from the scheme of control without motivations (Fig. 8) to the scheme with motivations (Fig. 9) can be considered as the emergence of a new level of hierarchy in the control system of an agent. This transition is analogous to the metasystem transition from simple reflexes to complex reflex in the metasystem transition theory (Turchin, 1977).

Thus, the model demonstrates that simple hierarchical control system, where simple reflexes are controlled by motivations, can emerge in evolutionary processes, and this hierarchical system is more effective as compared to behavioral control governed by means of simple reflexes only.

4.2. Model of evolution of web agents[3]

The goal of the model is to analyze evolution and self-organization of Alife agents in Internet environment. The model is similar to previous one. The main particularities (characterizing new features as compared with the model of the section 4.1) of the current model are:

- The model implies that there is a set of Web World lobes, where a population of Alife agents evolves. Each lobe contains a sub-population of agents (Fig.10). *The lobes are distributed in an Internet environment.*
- Agents can *communicate* each with others. Agents can *fly* between different lobes. Agents can execute several actions; in particular, they can *solve tasks*. Solving a task, the agent obtains certain reward.
- Agents have two needs: *the need of energy and the need of knowledge*. Any need is characterized by a quantitative motivation parameter.
- There are *two neural networks* that control behavior of an agent. The first neural network governs *selection of actions* of the agent. The second neural network governs *solution of tasks*. There is a procedure of learning of the second neural network. This learning is based on some modification of

[3] This model was developed together with Benjamin N. Goertzel and Yuri V. Macklakov. The work on the model was supported by Webmind, Inc. See B.N. Goertzel et al (2001) for more detailed description of the model.

well-known back-propagation method (see below). The synaptic weights of the first neural network don't change during agent life.
– The synaptic weights of the first neural network and initial synaptic weights of the second neural network are genes of the *two chromosomes* of the agent.

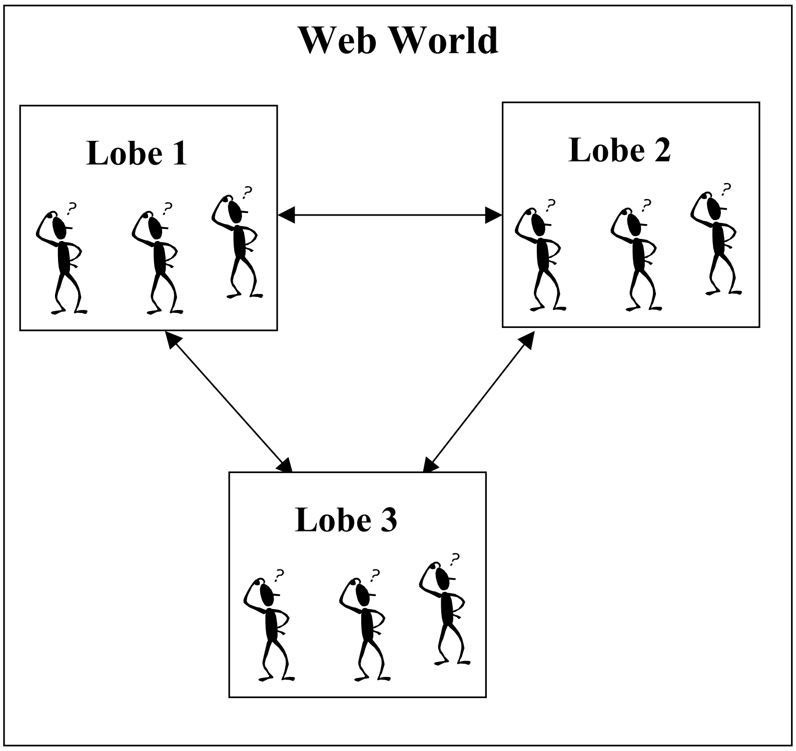

Fig. 10. Alife agents distributed in Internet.

The model implies that any agent has its internal energy resource. Executing an action, the agent spends its energy resource. When internal energy resource of an agent goes to zero, this agent dies. Any agent can eat food and replenish its internal energy resource. However, before eating, the agent should solve some task. The value of the reward that the agent obtains depends on quality of task solution. Rewards can be positive or negative. Receiving positive reward, the agent eats food and increases its energy resource. When the agents receives negative reward (punishment), its energy resource is decreased.

Agents can communicate each with others. Communicating, agents help each other to increase their knowledge about situations in different lobes.

In any lobe, agents can mate each other. Executing the action "Mating", an agent becomes a partner for mating. Two partners for mating in the same lobe give birth to a child. Each parent transmits to the offspring some part of its energy resource. Each chromosome of the offspring is obtained through one-point crossover of the corresponding chromosomes of the both parents. Additionally, there are small mutations of the genes of chromosomes.

Flying between lobes, agents are able to travel over the Web World.

There is a rather non-trivial procedure of learning of the second neural network (the network of the task solver). This learning is based on the complementary reinforcement back-propagation, described by D. Ackley and M. Littman (1990, 1992).

Omitting some inessential details, we can describe the method of learning as follows. The architecture of the neural network is the same as in usual back-propagation method (Rumelhart et al, 1986): the network has the layered structure; neurons have the logistic activation function. Suppose that at given moment of time, input and output vectors of the neural network are **X** and **Y**, respectively. Note that according to logistic activation function of neurons, values of components Y_i of the output vector **Y** belong to the interval (0,1). If solving task, an agent obtains positive reward, then output vector is considered as target vector **T** = **Y**. If the agent obtains negative reward, then the target vector is "complementary" to the output vector: $T_i = 1 - Y_i$. Then usual backpropagation procedure is applied, and the mapping between input and target vectors **X** and **T** is reinforced. Thus, the complementary reinforcement back-propagation method reinforces/dereinforces such relations between **X** and **Y** that are positively/negatively rewarded.

We created a program that implements the model. The results of preliminary simulations demonstrated that evolving population of agent is able to find simple forms of adaptive behavior.

We can also note a possible practical direction of development of the model. Let's consider a population of high-tech companies. Each company has a computer network; this network is the lobe, where a corresponding sub-population of agent evolves. Any company has a special person, the supervisor of sub-population of agents. This supervisor gives some practical tasks to agents in his lobe and rewards or punishes them. Tasks could be such as «give me prognosis of this certain market» or «find me good partner for this kind of cooperation», etc. Agents should solve tasks and are rewarded/punished accordingly. Agents have access to Internet. Companies have web-sites, so agents are able to analyze information about the population of companies. During an evolution of the population of Web agents, tasks for agents may be made more and more complex and this could ensure more and more intelligent behavior of agents.

Of course, the described two models are only simple examples of concrete researches. In the next section, we will outline a possible way from these simple models to implementation of higher cognitive abilities.

5. Towards to implementation of higher cognitive abilities

Let's consider possible steps toward modeling high level intelligence.

Step 1. *Evolutionary optimization* of simple instinctive behavior. We can code a control system of an agent (e.g. agent's neural network) by means of a genome and optimize the genome by means of an evolutionary method. For example, we can introduce a parameter of vital resource R of an agent; resource is increased/decreased at a successful/unsuccessful action of the agent. If resource of the agent goes below certain threshold, the agent dies; if agent's resource is large, the agent gives birth a child (deterministically or in some stochastic reproductive process), reproducing (and modifying by mutations) its genome. The model of the section 4.1 is the example of this level of implementation.

Step 2. Using the concept of internal vital resource R, we can introduce the *natural scheme of unsupervised learning*. Suppose that the control system of an agent is a layered neural network with logistic activation function of neurons. Then this control system can be optimized *at each action* of the agent by means of the complementary reinforcement back-propagation method (described in the section 4.2). If the action of the agent is successful ($\Delta R > 0$), the synaptic weights of the neural network are reinforced; if the action is unsuccessful ($\Delta R < 0$), the synaptic weights are dereinforced.

This method can be complemented with usual evolutionary optimization: initial (obtained at the birth of an agent) synaptic weights of the neural network can constitute the genome of the agent. Method of evolutionary optimization of the agent genome is the same as described above (Step 1).

Step 3. We can consider several vital needs of an agent (energy, security, reproduction, knowledge), characterizing j-th need by its own resource R_j and motivation M_j (j =1,2, …, n). It is natural to assume that a motivation M_k monotonically decreases with increasing the corresponding resource R_k. Supposing that at each moment of time there is a *dominating motivation* M_d that determines the agent behavior, we can introduce the scheme of unsupervised learning for this case too. Namely, if the resource R_d , corresponding to dominating motivation, increases/decreases, then synaptic weights of the neural network of the agent are reinforced/dereinforced. Note, knowledge can be considered as an important need of the agent (Zhdanov 1998), implying that intellectual curiosity is the motivation to increase knowledge.

Step 4. We can imaginary reorganize the scheme of modeling of the Step 3, trying to approach to a scheme of P.K. Anokhin's functional system (see the section 3.2.2). We can consider an animat (or animal, or model of animal) that has rather arbitrary structure of the neural network. There are different links in the network with different weights between neurons. The animat has needs and corresponding motivations M_j as above. However, now we assume that the animat can have also a model of the external world and it can make prognosis of results of its actions.

We can suppose that at given dominating motivation M_d (e.g. the motivation to get food) some excitatory processes take place in the neural network. Excitatory processes can restore in neural memory patterns of objects that are related to satisfaction of the need (e.g. the pattern of meat) and patterns of situations, at which these object were observed. (It is not difficult to imagine these patterns – the patterns can be stored in the form of Hebbian assemblies.) Taking into account this information, our animat can try to make a prognosis about results of its possible actions. This process of prognosis is rather non-trivial. However, imagine that our animat is able to make a prognosis. We can also imagine that the animat is able to select an adequate action in accordance with the prognosis. Then we can naturally suppose that the animat is able to learn by means of modification of its neural network. If the action is successful, that is the foreseeing result is achieved, then the existing links in the neural network are reinforced by corresponding modification of synaptic weights. Otherwise, some unlearning procedure could take pace, e.g. in the form of some dereinforcement as discussed above in Steps 2, 3.
In addition, we can imagine a set of Hebbian assemblies in the neural networks of animats; assemblies store patterns of neuron activities that characterize notions, names or concepts. Assemblies store patterns in the form of associative memory, so assemblies memorize the most general and statistically averaged notions (Kussul, 1992). The set of assemblies connected by neuron links can be considered as a semantic net. We can imagine that, using the semantic net, the animat is able to make some "logical" inferences, similar to that of discussed in the section 2 and in the draft paper by B.N. Goertzel (2002).

Thus, we can imagine a non-trivial neural-network-based control system of animats. Using this control system, an animat is able to construct models of environment, to make "logical" inferences, to predict results of its actions. The animat is also able to learn; links in animat's neural network are changed during learning. We can also imagine that neural network architecture of animats can be optimized by ontogenetic development and evolutionary optimization in population of animats. We can consider the intelligence of such animats as "dog-level" intelligence.

Of course, the Step 4 is quite imaginary. However, the described conceptual scheme of animat control system is sufficiently concrete and can stimulate researches of animat intelligence and developments of real AI systems.

Moreover, we can go further to some fantastic step.

Step 5. Can we try to imagine a metasystem transition from "dog-level" intelligence (outlined in the Step 4) to human level intelligence? Yes, we can. Let's suppose that there is a *society* of animats, each animat has a neural network control system. Animats are able to create models of the external world and make inductive logical inferences about the world; they are able to make prognosis and to use forecasting in their activity. Suppose that animats can communicate each other (similar to agents of the model of the Section 4.2). Their communications could help them to produce collective actions. Therefore, communications could result in some "animat language"; and the notions, corresponding to words of this language, could solidify in animats memories. These animats could also invent numerals in order to use calculations in planning collective actions. Thus, such animats could have *primitive thinking*, similar to thinking of hunter tribe of ancient men. Let's suppose now that there is some sub-society that would like to create most strongest form of thinking, to think about thinking, to create a special language about thinking. Such animats could be considered as mathematicians and philosophers of animat society (similar to mathematicians and philosophers of Ancient Greece). This step from the primitive thinking to the *critical thinking* is an important metasystem transition to human level intelligence (Turchin, 1977). Of course, this step is quite fantastic, nevertheless, we can imagine and even try to model it.

6. Conclusion

This chapter has mainly conceptual, philosophical character. Nevertheless, I hope that it could stimulate developments of concrete models of "intelligent" adaptive behavior. In my opinion, modeling of intelligent features outlined in the Step 4 of the section 5 would the most interesting and important from both scientific and AI application points of view.

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