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Alexei V. Samsonovich
Valentin V. Klimov
Galina V. Rybina *Editors*

Biologically Inspired Cognitive Architectures (BICA) for Young Scientists

Proceedings of the First International Early Research Career Enhancement School (FIERCES 2016)

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Janusz Kacprzyk, Polish Academy of Sciences, Warsaw, Poland
e-mail: kacprzyk@ibspan.waw.pl

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Editors
Alexei V. Samsonovich
Department of Cybernetics
National Research Nuclear University
Moscow
Russia

Valentin V. Klimov
Moscow Engineering Physics Institute (MEPhI)
National Research Nuclear University
Moscow
Russia

Galina V. Rybina
Moscow Engineering Physics Institute (MEPhI)
National Research Nuclear University
Moscow
Russia

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Preface

First School on Biologically Inspired Cognitive Architectures

The emergence of biologically inspired cognitive architectures (BICA) challenges researchers across many disciplines with a new frontier: computational replication of the human mind, taken in all its essential aspects, as a functional unit of a team or a society, based on a biologically inspired approach (the BICA Challenge). After many decades of successful progress in the field of artificial intelligence, we understand now that this approach is necessary, because essential qualities of biological intelligent systems like robustness, flexibility, adaptability, communicability and teachability are still unmatched by their artificial counterparts.

This volume includes papers from the First International Early Research Career Enhancement School on Biologically Inspired Cognitive Architectures: FIERCES on BICA 2016. It is a fierce attack on the challenge, and historically, the first international school on BICA. Its mission is to facilitate interaction and collaboration among top experts in the field (including such names as Christian Lebiere, Frank Ritter, Paul Verschure) and young researchers who devoted themselves to solution of the BICA challenge, by bridging cross-disciplinary, cross-generation, and cross-cultural barriers.

Biologically Inspired Cognitive Architectures (BICA) are computational frameworks for building intelligent agents that are inspired from biological intelligence. Thanks to modern brain imaging and recording techniques allowing us to map brain structures and functions, our present ability to learn from nature how to build intelligent systems has never been greater. At the same time, new techniques developed in computer and cognitive sciences conveniently complement biological inspirations, allowing us to build the software that will unleash the presently available at low cost computational powers to their full extent. Given this situation, an explosion of intelligent applications from driverless vehicles, to augmented reality, to ubiquitous robots, is now almost certain. As a consequence, this first school on BICA is interdisciplinary in nature and promises to yield bidirectional flow of understanding between experts in all involved disciplines.

Topics of articles included in this volume extensively cover the most advanced scientific fields relevant to BICA that are traditionally considered at the international level of significance and discussed at many mainstream national and international conferences on artificial intelligence, neuroscience, and cognitive modeling, including conferences organized by the Russian Association of Artificial Intelligence (RAAI) and by the BICA Society. The list of the latter is quite long. Beginning with the AAAI Fall Symposia on BICA (2008, 2009), the Annual International Conference on BICA has been held every year since 2010, demonstrating progressively growing popularity. Locations of the conference included Arlington, Virginia (near Washington, DC, 2010); Palermo, Italy (2012); Kiev, Ukraine (2013); Cambridge, Massachusets (2014); Lyon, France (2015); and upcoming this year—New York, USA (2016). The present BICA event, however, is unique in its kind.

Specifically, papers included in this volume are a mixture of tutorials and research articles, focused on fundamental and applied areas of cognitive, social and neurosciences and artificial intelligence, including, but not limited, to topics such as cognitive modeling, automated planning and behavior generation, fuzzy models and soft computing, knowledge engineering, ontologies and knowledge management, acquisition, representation and processing of temporal knowledge, applied intelligent systems, dynamic intelligent systems and real-time systems, intelligent tutoring systems, instrumental systems for artificial intelligence. All works included in this volume have been carefully peer-reviewed and refereed, and reflect the high level of ongoing research and development in participating leading universities and research centers around the world, including those in the US, France, Germany, Italy, Spain, Japan, Ukraine, Belarus, and also in Russia (Moscow, St. Petersburg and other Russian cities).

We are grateful to all authors who contributed their works to this volume. We also would like to express our many thanks to all people who helped us with the organization of the first school FIERCES on BICA, primarily including Drs. Aleksandr I. Panov, Olga A. Mishulina, Vladimir G. Redko, Galina A. Beskhlebnova, Ilya Sukonkin, and Ms. Olga N. Petukhova. Last, but not the least, is our appreciation and acknowledgment of the sponsors of FIERCES on BICA. Financial sponsorship was provided by the Russian Science Foundation (Grant No 15-11-30014 to Dr. Alexei V. Samsonovich). Organizational support was provided by Department of Cybernetics of the National Research Nuclear University MEPhI (Moscow Engineering Physics Institute): https://mephi.ru/eng/about/departments/22.php, with the help of BICA Society (http://bicasociety.org).

Moscow, Russia
February 2016

Alexei V. Samsonovich
Valentin V. Klimov
Galina V. Rybina

Contents

The Cognitive Architecture Within the Natural-Constructive Approach

Olga Chernavskaya

Abstract The cognitive architecture designed within the natural-constructive approach to modeling the cognitive process is presented. This approach is based on the dynamical theory of information, the neurophysiology data, and neural computing (using the concept of dynamical formal neuron). It is shown that this architecture enables us to interpret and reproduce peculiar features of the human cognitive process, namely—uncertainty, individuality, intuitive and logical thinking, etc. It is shown that the human emotions could be interpreted as the *derivative* of the noise amplitude, with the absolute value reflects the degree of emotional reaction, while its sign corresponds to negative or positive emotion, respectively; thereby wide spread binary classification gets natural explanation.

Keywords Generation of information · Noise · Image · Symbol · Emotions · Learning

1 Introduction

The problem of comprehension and modeling a cognitive process does attract permanent interest and represents a pronounced example of the inter-disciplinary problem [5, 18, 22]. Indeed, the comprehension of the brain-activity mechanism requires knowledge in physics (as any substantial system), biology (living system), as well as psychology and philosophy (*thinking* and *speaking* system). Recently, new specific direction called "cognitology" has been formed to join both these scientific blocks related to the brain and mind, respectively, with accounting for the "explanatory gap" between them. Within this direction, there are various approaches to modeling a cognitive process (e.g., [16, 20, 23]. In our works [1–3] we have elaborated so called Natural-Constructive Approach (NCA), which is based on the Dynamical Theory of Information (DTI), elaborated in [5, 9], neurophysiology data

O. Chernavskaya (✉)
P. N. Lebedev Physical Institute, Russian Academy of Sciences, Moscow, Russia
e-mail: olgadmitcher@gmail.com

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[21], and neural computing [10] combined with the technique of nonlinear dynamic differential equations. This approach is aimed to modeling just the human-level cognition.

It is important to stress that the majority of popular imitation models are focused on constructing the systems that are capable to execute certain set of functions *better* than humans do. In this process, the priority refers to *reliability, effectiveness* and *processing speed* of the models proposed. Nevertheless, presently it becomes clear that this approach is not completely relevant for modeling just the human cognition. Actually, a human person, being posed to various real situations, should be able to solve a lot of various problems (including the ill-posed ones). Thus, the priority is to be given to the ability to "survive", i.e., to *adapt* to unexpected and unpredictable situations. Therefore, a human-level cognition is *uncertain,* often *unpredictable*, and always *individual.* The enigma of individuality (in particular, of the artificial systems) is really the challenge for modeling a cognitive process.

Regarding human-level cognition, one cannot ignore the role of emotions. There are numerous attempts to consider the emotional component in modeling the cognitive process (e.g., [13, 14, 20]). However, the exact mechanism of emotion emergence, as well as the character of mutual influence of cognitive and emotional components were not revealed.

Another key problem in the cognition modeling concerns the imitation and interpretation of the logical and intuitive thinking. It is close to the "enigma of two hemispheres": why a human brain is splitting into two constructively similar but still not identical parts. The hypothesis has been put forward (and became popular) that the right hemisphere (**RH**) is responsible for learning, while the left one (**LH**) does operate with the well-known information [7]. Below, it will be shown that this hypothesis is in entire agreement with our inferences.

Note that there is no unambiguous definition of the cognitive process. Within NCA, the cognition is treated as a *self-organizing process of recording, storing (memorization), coding, processing, generating, and propagating the "self" information.*

In the present work, we propose a particular version of cognitive architecture designed within NCA to perform these functions.

2 Theoretical Foundation of NCA

2.1 Dynamical Theory of Information (DTI) as Applied to Cognitive Process

- The definition [19]: *information is the memorized choice of one version among a set of possible and similar ones*. This definition does not contradict to others, but gives an idea of ***how*** the information might emerge;
- The choice could be made as a result of two different processes, namely—*reception* (superimposed choice) and *generation* (free choice) of information.

These processes are *dual* (complementary), thereby, these functions are to be shared between just two different subsystems (below: hemi-systems).
- The process of generation of information could proceed only in the presence of chaotic (casual) element, commonly called the *noise*.
- Depending on ***who*** makes the choice, there appear: *objective* information (the choice made by Nature, i.e., physical principles) and ***conventional*** information (the choice made by certain *collective*). This choice is not *the best* but *individual* for a given group.

2.2 Neurophysiology Considerations

- Neuron is a complex structure not reduced to a simple adder of signals, as it is accepted in standard neural processors. Within NCA, we use a continual representation for the *dynamical formal neuron* [2]—a particular case of the FitzHugh-Nagumo model [6, 17].
- Emotions are controlled by the level and composition of *neural transmitters* inside the human organism.

2.3 Neural Computing

- The neural processor represents a plate populated by the *dynamical* formal neurons described by the nonlinear differential equations [2, 3].
- Imaginary information should be recorded and stored within the Hopfield-type [12] processor (*distributed* memory) providing associative correlations.
- Recording the information (learning) requires Hebbian training mechanism: initially weak connection become stronger ("blacker") in course of the learning process [11].
- Storage and processing the well-known information (recognition, prognosis, etc.) require the training rule proposed by Hopfield [12]: all connections are initially equal and strong; during the training process the "irrelevant" connections are gradually *frozen out* (the principle of "redundant cut-off").
- The conversion of an image into *symbol* is to proceed in the localization Grossberg-type [8] processor with nonlinear competitive interactions. This provides the choice of single neuron (symbol) to represent all the information on a given image. Here, the paradigm "Winner Take All" should be realized [15]. Within NCA, this process should be *unstable* to secure unpredictable symbol position. This feature secures the *individuality* of a given system.
- After the given *G*-neuron became the *symbol*, it should be eliminated from the competitive struggle and acquires the possibility to cooperate with other neuron-symbols to form the *generalized* image ("image-of-symbols"). Free G-neurons could compete only.

3 Cognitive System Architecture

3.1 Main Constructing Principles

The version of NCA architecture presented in Fig. 1 has been worked out in the paper [2]. The main constructive feature of this architecture consists in splitting the whole system into two (similar) hemi-systems: **RH** (Right Hemi-system) containing the noise, and **LH** (Left Hemi-system) free of noise. The terms are chosen to correlate conventionally with cerebral hemispheres. The noise in **RH** provides generation process, i.e. production of *new* information and *learning*. **LH** is responsible for reception and processing the already known (learned) information. This specialization, being the theoretical result of DTI principles only, surprisingly coincides with inference of practicing psychologist Goldberg [7]. This fact represents a pleasant surprise and indirect confirmation of NCA relevance.

All the connections in R**H** are training according to the Hebb's rule [11]: being initially weak, the connections become stronger ("blacker") during the learning process up to certain threshold value. Then the learned image is transferred to **LH**. In **LH**, on the contrary, all connections are trained according to original version of Hopfield [10] "redundant cut-off". Thus, **RH** provides the *choice*, while **LH** performs the *selection.*

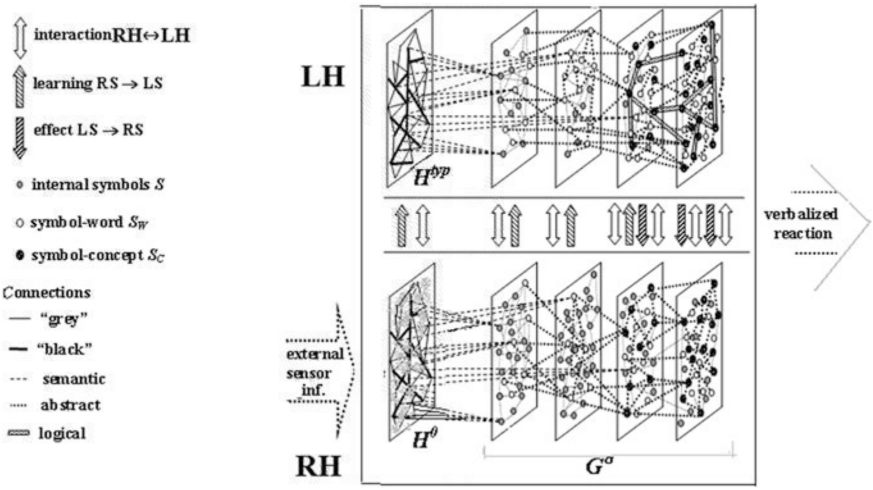

Fig. 1 Architecture of the cognitive system

3.2 Representation of Different Information Levels

The whole system represents complex multi-level structure that does evolve by itself (in Figure—from the left to the right) due to the self-organizing principle of "connection blackening". This implies that at each level, the elementary act of the image processing in **RH** and transferring to **LH** is repeated. In physics, there is special term "scaling" for such principle of organization, and the result is called a *fractal.* The system contains four basic elements.

– *Primary image* $\boldsymbol{I}$ at the plate $\boldsymbol{H}^{\boldsymbol{0}}$ include any available imaginary information: all signals from receptors are written as chains of activated neurons forming the ***images***. The inter-plane connections between neurons are modified from weak (grey) to strong (black) ones upon presentation of the objects. This level carries out the function of *recording* the "sensual" information and refers to **RH**.
– *Typical images* ***TI*** are presented at the plate $\boldsymbol{H}^{\mathrm{typ}}$ in **LH,** which perceives only the images recorded by strong enough (black) connections. Its functions are: to store useful information and filter out unnecessary one, and to recognize already learned images.
– *Symbolic* (*semantic*) *information—symbols* ***S*** correspond to *typical* images and are formed in **RH** (with the noise participation). Each symbol possesses a semantic content, i.e., awareness of the fact that this chain of active neurons describes a real particular object. At the same level one can find a ***standard symbol*** (symbol-word $\boldsymbol{S}_{\boldsymbol{W}}$ that are presented in **LH** mainly) to indicate the same specific object. Symbols provide the interaction between the plates, i.e., processing of sensible information.
– *Abstract* (*verbalized*) *information*—whole infrastructure of symbols ***S***, standard symbols $\boldsymbol{S}_{\boldsymbol{W}}$, and their interrelations. These items are not connected with neurons-progenitors on the plates ***H***, and thus, are not associated with any imaginary object, but appear in the well-trained system due to interaction of all the plates (the "deduced knowledge"). Its function is to implement a communication with other systems ("*to explain by words*") and comprehend the symbolic information. The highest hierarchy levels are occupied by the *generalized symbols*, or *symbol-concepts* $\mathbf{S}_{\mathbf{C}}$, such as "conscience", "beauty", "infinity", etc. These symbols have no material content (real concrete object), but do have sense for a given system.

3.3 Interpretation

The emergence of each subsequent level is accompanied by a *reduction* of information. So, primary images recorded by weak (grey) connections are not transferred to $\boldsymbol{H}^{typ}$ level, and thus, could not be associated with any symbol—this information turns out to be neither conscious, not controlled by the system itself. This chain can be activated by noise only, what corresponds to an *inspiration* (the "aha moment"). The whole set of "grey images" could be treated as the *sub-consciousness*.

The lower levels of the architecture represent the *latent* (hidden) individual information of the system, the "thing-in-itself". Only the higher levels, the *abstract verbalized* information make sense in the common meaning ("*to bring on the level of consciousness*").

Note that the *latent* (hidden*)* information has its own "levels of depth", with the bulk being stored in **RH**. This very information could be interpreted as the basis for *intuition*. The *logical* thinking should be related to *verbalized concepts* and *abstract relations*, but those that are common for a given society. It refers to **LH** only.

4 Representation of Emotions

4.1 The Problem of Emotion Formalization

Incorporating the emotions into artificial cognitive system represents really the challenge, since emotions have dual nature. On the one hand, they represent *subjective self-appraisal* of the current/future state. On the other hand, emotions are associated with *objective* and experimentally *measured* composition of neural transmitters in the human organism. The latter is controlled by more ancient brain structures (so called "old cerebrum") than the neocortex. Since the cognitive process is commonly attributed to the neocortex, the realization of mutual influence of these structures requires special efforts. Thus, there is the same explanatory gap, as between the concepts of brain and mind.

In psychology, the self-appraisal (emotion) is ordinarily associated with achieving a certain *goal*. Commonly, they are divided into positive and negative ones, with increasing probability of the goal attainment leading to positive emotions, and vice versa. Furthermore, it is generally known that any *new* (*unexpected*) thing/situation calls for *negative* emotions, since it requires additional efforts to adapt. Our representation of emotions relies on this concept as well.

In neurophysiology, emotions are controlled by the level and composition of the *neurotransmitters* inside the organism. The entire variety of neurotransmitters can be sorted into two groups: the *stimulants* (like *adrenalin*, *caffeine*, etc.) and the *inhibitors* (*opiates, endorphins*, etc.). However, there is no direct correspondence between, e.g., positive self-appraisal and the excess of either inhibitors, or stimulants.

According to DTI, emotions should be classified as *impulsive* (useful for generation of information) and *fixing* ones (effective for the reception of information). Since the generating process requires the noise, it seems natural to associate impulsive emotions (*anxiety, nervousness*) with the *growth of the noise amplitude.* Vice versa, fixing emotions could be associated with *decreasing* noise amplitude (*relief, delight*). By defining the goal of the living organism as the maintenance of *homeostasis*, (i.e., calm, undisturbed, stable state), one may infer that, speaking very roughly, this classification could correlate with negative and positive emotions, respectively.

4.2 Main Hypothesis Concerning Emotion Representation Within NCA

Proposition 1 *The influence of neurotransmitters should be accounted for by the system of equations that link the noise amplitude Z(t) with the aggregated variable μ(t) that represents virtual composition (stimulants minus inhibitors) of neurotransmitters.*

Proposition 2 *The emotional reaction of human beings could be interpreted as the time derivative of the noise amplitude, i.e., dZ(t)/dt. The absolute value of derivative dZ/dt corresponds to the degree of emotional manifestation: drastic change (jump) in Z(t) imitates either panic (dZ/dt > 0), or euphoria (dZ/dt < 0), and so on. Note that this value could be either positive, or negative that could be (very roughly) related to negative and positive emotions, respectively.*

Proposition 3 *The same derivative should control the "dialog" between hemi-systems: increasing Z(t) (negative emotions) corresponds to activation of* ***RH****, while decreasing Z (t) (positive emotions) switches on* ***LH*** *activity.*

Basing on these propositions, we have elaborated the model for mutual influence of the "emotional" and "cognitive" factors [3, 4] that reveals a wide field for speculations and interpretations. Further study of this model seems promising.

5 Conclusion

The cognitive architecture designed within NCA represents a complex multi-level construction of different type neural processors, capable to perform the functions of recording, memorization, coding, processing and generation of the information. The emotions are treated as the variation of the noise amplitude that should help to activate or, vice versa, set at rest the cognitive process; they are inherently embedded into the system from the very beginning.

It should be stressed that the approach presented contains *three principle presumptions* that distinguish it from other ones. First, the main principles of DTI being applied to a cognitive process result in inference that the whole system *should by split into two* independent but linked hemi-systems for generation and reception of information, an analogy to cerebral hemi-spheres. Second, the process of generation of information requires *participation of the random element* (*noise*). Third, the learning principles in those hemi-systems *should differ*: generation of information requires Hebbian training rule, while the reception requires Hopfield-type training. These very features enable us to interpret and imitate the human-level cognitive features, namely—uncertainty, individuality, capability of intuitive and logical thinking, emotional effect on a cognitive process, etc.

However, there are still problems to be considered, such as social behavior, decision making, etc. Those problems deserve further research.

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Models of Autonomous Cognitive Agents

Vladimir G. Red'ko

Abstract The lecture describes current models of autonomous cognitive agents. The study of these models can be considered as the method of investigations of biologically inspired cognitive architectures (BICA). The main attention is paid to the models that are used at studying of cognitive evolution. Several examples of such models are outlined. Schemes of new models are proposed.

Keywords Models of autonomous cognitive agents · Modeling animal behavior · Evolutionary origin of human cognition

1 Introduction

One of the main methods of BICA investigations is the study of models of autonomous cognitive agents. We consider an autonomous agent as a modeled organism. The review [1] characterizes early researches of cognitive agents. Our approach is in close relation with investigations of cognitive evolution [2, 3]. The current lecture describes shortly the following models:

- the computer model of adaptive behavior of autonomous agents that have natural needs: food, safety, and reproduction [4];
- the model of formation of heuristics and generalized notions by the self-learning agent [5];

V.G. Red'ko (✉)
Scientific Research Institute for System Analysis, Russian Academy of Sciences, Moscow, Russia
e-mail: vgredko@gmail.com

V.G. Red'ko
National Research Nuclear University MEPhI (Moscow Engineering Physics Institute), Moscow, Russia

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- the models of agent movement in mazes, accumulation of knowledge, and formation of predictions [6];
- the model of plan formation of rather complex behavior [7].

In addition, we propose schemes of new models of autonomous cognitive agents that could do scientific discoveries [8].

2 Examples of Models of Cognitive Agents

2.1 Model of Autonomous Agents with Several Natural Needs

We believe that an agent has the needs of food, safety, and reproduction. We consider the population of agents. Each agent has the internal resource $R(t)$. The time t is discrete. Each agent is placed in a certain cell; there is a predator in the same cell. The predator activity varies periodically: after every T_p time moments, the active predator becomes inactive; the inactive predator becomes active. The active predator can reduce essentially the resource R of the agent that is in the predator cell.

There is the hierarchy of needs: the need of food has highest priority, the need of reproduction has the lowest priority.

Satisfaction of agent needs is regulated by means of three factors F_F, F_S, F_R, related to needs of food (F_F), safety (F_S), and reproduction (F_R). We believe that there is a threshold for each factor (T_F, T_S, T_R). If a certain factor is greater than the corresponding threshold, then the related need is satisfied. The agent has the leading need, which has the highest priority among unsatisfied needs.

The agent control system is a set of rules: $\boldsymbol{S}_k \rightarrow A_k$, where $\boldsymbol{S}_k$ is the situation, A_k is the action, k is the rule index. Each rule has its own weight W_k. The agent rule weights W_k are adjusted by means of the reinforcement learning [9]. The change of the factor of the leading need is the reward of the agent. The agent prefers the actions that correspond to large rule weights W_k. The situation vector $\boldsymbol{S}_k$ characterizes (1) the predator activity in the agent cell, (2) the previous agent action, (3) the leading need of the agent. The agent can execute the following actions: (1) searching for food, (2) to eat the food, (3) preparation for reproduction, (4) reproduction, (5) to do defense action, (6) to do nothing (to rest).

At eating food, the agent increases its resource R. At reproduction, the agent transmits an essential part of its resource R to its descendant. The agent-child inherits the rule weights W_k of the parent with small variations. If the agent executes the action "defense", it is protected from the active predator that is in the agent cell, whereas, the active predator reduces essentially the resource of the non-defensive agent.

The computer simulation demonstrates the cyclical behavior of agents. During the cycle, the agent firstly accumulates the internal resource (by eating the food), then the agent's actions are aimed at maximizing the safety and maintaining the level of internal resource, and when both needs (food and safety needs) are satisfied, the agent replicates (the need of reproduction is satisfied too).

Thus, the behavior of autonomous agents that have several natural needs has been analyzed. The model demonstrates the formation of cycles of behavior; the needs of food, safety, and reproduction are consecutively satisfied in these cycles.

2.2 Model of Formation of Heuristics and Generalized Notions by Self-learning Agent

One of the most important cognitive properties of living organisms is the formation of generalized notions. Using notions leads to a reduction in the required memory and the processing time. However, how do the notions emerge? Can we imagine the processes of formation of notions by means of computer simulation? We outline a computer model in which the autonomous agent alone produces generalizations and forms notions.

The model describes behavior of the autonomous agent in the two-dimensional cellular world. The control system of the agent is a set of rules: $\mathbf{S}_k \rightarrow A_k$, where $\mathbf{S}_k$ is the situation, A_k is the action, k is the index of the rule. Each rule has its own weight W_k. The vector $\mathbf{S}_k$ characterizes presence or absence of food in cells in the "field of vision" of the agent. The field of vision includes four cells: the cell, in which the agent is, the cell ahead of the agent and the two cells to right and left from the agent. The agent executes one of the following five actions: eating food, moving forward, turning to right or left, to rest. Portions of food are randomly placed into a half of the cells of the cellular world. The agent resource R increases at eating food.

Rule weights W_k are modified by means of the reinforcement learning [9]. Changes of the agent resource R are rewards at this learning. The reinforcement learning increases the weights of the rules, the use of which leads to an increase of the agent resource. The agent prefers the actions corresponding to large rule weights W_k.

The computer simulation demonstrates that the self-learning agent itself generates the following heuristics. The agent executes the action *eating food*, if there is food in the cell containing the agent (irrespective of presence of food in the other cells of the field of vision of the agent). The agent executes the action *moving forward*, if there is no food in the agent cell, and there is food in the ahead cell. The agent executes the action *turning to right or left*, if there is no food in the agent cell and in the forward cell, but there is food in the right or left cell from the agent. The frequency of the action *to rest* is negligible small.

In addition, the computer program included the averaging procedure. Namely, the average number of executions of certain actions for a given situation $\mathbf{S}$ was calculated. The averaging procedure results in creation of the following agent notions: *there is food in my cell*, *there is food in the forward cell,* and *there is food* *in the right or left cell*. Therefore, the agent itself is able to generate autonomously the notions, characterizing the sensory information.

2.3 Models of Fish Exploratory Behavior in Mazes

We designed and analyzed models of cognitive behavior of fish in the course of maze exploration. The models are inspired by the biological experiment on zebrafish, Danio rerio, in mazes [6]. Three types of models are designed and investigated. The model 1 describes how the fish acquires knowledge about arms of the maze. The model 2 characterizes fish's predictions of the next situation for the current situation and action. The model 3 is the hypothetical model of plan formation in a rather complex maze.

The model 1 assumes that the agent (modeled fish) has a certain knowledge K_i about each arm. When the agent visits i-th arm, the value K_i becomes equal to certain maximal value. Additionally, all values K_i slightly decrease with time.

The model 2 characterizes assurance of agent predictions. Namely, for the given initial situation S_t (each situation corresponds to a particular arm) and the action A_t (moving forward, turning to left or right) the assurance of the prediction of the next situation S_{t+1} is characterized by the value A_S. The values of assurances A_S are adjusted as follows. At the time step $t + 1$, the agent checks the prediction that it has made at the time step t. If the prediction of the next situation is correct, then the assurance of this prediction increases; if the prediction is wrong, then the assurance of this prediction decreases.

The model 3 assumes that after certain period of maze exploration, the fish is able to form some generalized notions that characterize the essential places (situations) in rather complex maze. The agent has knowledges about situations and reliable predictions of results of possible actions. The model 3 describes the process of forming the plan of movement to the goal situation, which was not visited for a long time (such situation has the minimal value of knowledge K_i). The agent creates a plan of movement from some starting situation to the goal situation.

The agent creates this plan as follows. Using the table of reliable predictions, the agent begins to analyze such situations and actions that result in the goal situation. Then the agent analyzes situations and actions that result in the pre-goal situations, and so on. Thus, *the agent begins from the goal situation* and analyzes consecutively possible ways to reach this situation. The agent also takes into account the distance from the considered situation S_t to the goal situation; this distance is the number of actions needed to reach the goal situation from the situation S_t.

Then the agent creates a simple *knowledge database* that is a table. Each row of this table includes the following information: (1) the given situation, (2) the action that reduces the distance between the given situation and the goal situation, (3) the next situation that is the result of the action and (4) distances between the given/next situations and the goal situation.

Finally, using this knowledge database, the agent forms a plan of movement from *the starting situation to the goal situation.* In this process of plan formation, the agent consecutively selects actions, which reduce the distance between the considered situation and the goal situation.

Thus, the models of accumulation of knowledge, prediction of results of actions, and planning of movement towards the goal situation have been developed and investigated.

The similar model of planning by New Caledonian crows is outlined below.

2.4 Model of Plan Formation by New Caledonian Crows

The model is based on the biological experiment on New Caledonian (NC) crows [10]. In that work, NC crows were preliminary trained to execute particular elements of a rather complex behavior. After the preliminary training, the crows should solve the three-stage problem that includes the following particular elements:

1. to pull up a short stick tied to the end of a string and to release this stick,
2. to extract a long stick from a barred toolbox by means of the short stick, and
3. to extract the food from a deep hole by means of the long stick.

It was impossible (a) to extract the food from the deep hole by means of the short stick and the bill, and (b) to extract the long stick from the barred toolbox by means of the bill. Therefore, in order to reach the food, the crow had to execute the ordered chain of sequential actions $1 \rightarrow 2 \rightarrow 3$.

Similar to the model of plan formation by fish, the agents (modeled crows) use the predictions of results of particular actions to create a *knowledge database*. The predictions were obtained during the preliminary training. The agent knowledge database characterizes situations, actions, results of actions, and distances between considered situations and the goal situation. The agent uses this knowledge database at forming the plan of solving the three-stage problem.

The process of plan formation was observed at computer simulation. See [7] for details.

The next section describes the scheme for future modeling of the autonomous agent-physicist (artificial scientist).

3 Proposal for Modeling of Autonomous Agent-Physicist

The proposal is based on the fact that *the most serious cognitive processes are processes of scientific cognition*. The background of this proposal is the report by Modest Vaintsvaig at the Russian conference “Neuroinformatics-2011” [11]; that report considers the models of an autonomous agent that tries to cognize elementary laws of mechanics. The agent observes movements and collisions of rigid bodies. Basing on these observations, the agent can generalize its knowledge and cognize regularities of mechanical interactions. Therefore, modeling of such autonomous agents, we can try to analyze, how agents could discover (by themselves, without any human help) elementary laws of mechanics. Ultimately, such agents could discover three Newton's laws of mechanics. Thus, we can investigate autonomous agents that could come to the discovery of the laws of the nature.

Using our knowledge about scientific activity of Isaac Newton, we can represent intelligence of such investigating agent in some details. The agent should have an aspiration for the acquisition of the new knowledge and for the transforming of its knowledge into compact form. The agent should have the curiosity that directs the agent to ask the questions about the external world and to resolve these questions by executing the real physical experiments. The agent should take into account the interrelations between different kinds of the scientific knowledge. It is natural to assume that a certain society of cognizing agents exists; the agent of the society informs other agents about its scientific results. For example, considering Isaac Newton as a prototype of the main agent, we can consider also agents that are analogous to Galileo Galilei, Rene Descartes, Johannes Kepler, Gottfried Wilhelm Leibniz, Robert Hooke. The agent should have the self-consciousness, the emotional estimation of the results of its cognition activity and the desire to reach the highest results within the scientific society. Agents should have the tendency to get the clear, strong and compact knowledge, such as Newton's laws or Euclidean axioms.

4 Conclusion

Thus, simple models of autonomous cognitive agents have been described. These models characterize initial steps of modeling of cognitive evolution [3]. The scheme of new models of the autonomous agent-scientists, which could cognize the nature, has been proposed.

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Differentiation of Groundwater Tax Rates as an Element of Improving the Economic Mechanism in the State Groundwater Extraction Management

Ekaterina Golovina, Maksim Abramov and Artur Azarov

Abstract Since Russia has rich resources of fresh underground waters, one of the major practical problems in their fund managing is a rational use of its resources and protection of aquifers from contamination and depletion. Economic instrument in the structure of state groundwater extraction management is a system of taxation. Modern system of groundwater extraction taxation is currently imperfect and has definite drawbacks. Among them are: incorrect system of tax rates for underground waters usage, budget deficit, that shifts to other areas of the national economy. The purpose of this article is the improvement of system of groundwater extraction taxation, which should be directed to the state for reimbursement of expenses for groundwater exploration, monitoring, and should provide differentiation of water tax rates, depending on hydrogeological characteristics of aquifers, types of water users and other parameters.

E. Golovina (✉)
National Mineral Resources University, Saint-Petersburg, Russia
e-mail: golovinakate21@mail.ru

M. Abramov · A. Azarov
St. Petersburg Institute for Informatics and Automation RAS, Saint-Petersburg, Russia
e-mail: mva16@list.ru

A. Azarov
e-mail: artur-azarov@yandex.ru

M. Abramov · A. Azarov
St. Petersburg State University, Saint-Petersburg, Russia

M. Abramov · A. Azarov
Moscow State Pedagogical University, Moscow, Russia

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1 Introduction and Related Works

Groundwater is classified as strategic mineral, along with hydrocarbon resources [10], so drinking water supply will become one of the urgent problems in modern society. According to UN experts, by 2030, about half of the world's population will suffer from a shortage of fresh water [11]. The territory of Russia has more than 20 % of world's reserves of fresh water, which makes it in this regard, one of the richest countries in the world [8]. The most promising source of drinking water supply is groundwater usage. Drinking and industrial groundwater is one of the most important components of the groundwater mineral resource base in the Russian Federation [7]. They are used to provide water supply to the population and the regional economy. According to official statistics, the share of groundwater use in overall balance of drinking water supply is 53–55 % [1]. Predicted reserves of drinking and technical groundwater of the Russian Federation are very large; they are estimated at 869.1 million m^3/day [7].

The current structure of water resources management in Russia is complex and "formless". Such issues as structuring of the management authorities, including clear delineation of roles, rights and responsibilities in organizations, as well as the division of competences among them; preparation of the legislative framework; development and implementation of economic mechanisms and methods in economic stimulation of rational groundwater usage should be solved in the course of water management restructuring [2].

Any changes in the system of state regulation of groundwater fund in Russia are impossible without improving the economic aspects of groundwater use, namely pricing and taxation system of groundwater extraction [6]. Current imperfect taxation system objectively counteracts the intensive reproduction of mineral resource base, integrated and rational use of groundwater [3]. Finally, the collection of groundwater tax does not provide even the current expenses of the state for monitoring and exploration. Therefore it is necessary to propose a new system of taxation, which depends on various parameters. Collection of groundwater tax should provide a self sufficiency for groundwater extraction branch and bring it from the category of the subsidized sectors in the national economy.

Development and improvement of groundwater extraction taxation through the use of differential calculation of groundwater tax rates for different categories of water users are the purposes of this article. There will also be an illustration of the calculating principles in the tax formula for a variety of parameters included in the proposed dependence.

2 The General Principle of Groundwater Tax Calculation

Nowadays, water tax has been provided for water that is being taken from surface and underground water and it depends on the economic regions of the country [9, 10]. What is more, tax rate is being differentiated by river basins and lakes in each economic region. At the same time, tax rates for underground water is also being differentiated by river basins and lakes, while this method is incorrect because one river basin can be discharged in several aquifers [5]. Furthermore, the geographical distribution of aquifers may affect multiple river basins. Each aquifer has its own properties, such as hydrodynamic characteristics, recharge and discharge zones, individual hydrochemical composition etc. That's why speaking about the main aspects in managing the extraction of groundwater, it is advisable to build a system of taxation in connection with the operation of individual aquifers or aquifer systems, taking into account their characteristics and geographical location, using a single tax rate for each aquifer [4].

Tax rate for the population water supply is 1.16 euros for 1000 m^3 of water. This tax rate is being indexed in association with the anticipated inflation ratio. However, total indexed rates of water tax without taking into account the peculiarities of the aquifer systems is contrary to the principle of respect to groundwater as unique useful fossil, and leads to averaging of aquifers, while they are different in their qualitative and quantitative characteristics.

One of the key problems in the system of groundwater taxation is water extraction account. Not all the groundwater intakes are equipped with water measuring meters, and those objects who have them, can easily be "got round". Especially, it is difficult to organize extraction account (calculation) for law-debit wells having a simple system of water piping for former and draw-wells, where it is impossible to take into consideration volumes of groundwater extraction. The same issue can be remarked with capping springs and overwhelming majority of private wells.

Solution of this problem can be found with application of water tax rate for estimated exploitative reserves of the intake. This parameter characterizes the size of stated water demand that can be extracted from the intake for the accounting period of time. When a license for groundwater extraction is granted, quantity of estimated exploitative reserves is the main parameter in al the hydrogeological calculations, including protective sanitary zones. Accordingly, directly this parameter is the key one during the calculation of water bearing stratum resource potential. Volume of groundwater extraction on the concrete water intake is subtracted from the total quantity of groundwater potential.

This principle of application of water tax rate for estimated exploitative reserves is similar to imputed tax. Quantity of water that is declared by the water consumer for supply will be taken into account in the calculating of water tax. For law-debit and individual wells it is advisable to calculate water tax rate due to the safe standards for drinking water (SanPin) for each region. Application of this approach will make people treat to exploitative reserves estimation, adequate request for water consumption and economy of mineral resources with special care. In the case of excess quantities of water consumption than values of estimated reserves water extracting company or individual person should feel responsibility that can be influenced by penal sanctions for resource overage. Herewith the role of state monitoring increases. Besides their functional purposes—collection of annual reports, control survey of groundwater intakes can be added.

The present system of water tax rates does not give any opportunities to the state as owner of mineral resources to make any revenues for the provision of such a valuable mineral as groundwater. Therefore new formula and algorithm for groundwater tax calculation are being proposed in this article. The basic variables of this formula are:

- The category of water user;
- The category of groundwater resource value;
- The category of complexity of the geological structure and hydrogeological conditions of the resources;
- The cost of ready-to-use groundwater (SST);
- Average regional water rates;
- The equity ratio (use factor).

Such parameters have been selected on the principles of hydrogeological zoning, aquifers' common characteristics and current criteria for the assessment of the extraction cost and treatment of groundwater.

The benefits that are being provided by these parameters are:

- Easy application;
- Official data (including statistics, monitoring of State Commission on reserves, etc.);
- Applicability of differentiation (based on the properties of the unique aquifers, types of water users etc.);
- Incentive effect (in terms of the water use disciplining);
- Conservation of groundwater resources;
- Generality: the ability to use collected water tax to finance "geological control" and the initial stage of exploration based on the conditions and characteristics of any region;
- The opportunity to supplement the methodology with new innovative technologies in geological prospecting.

The proposed formula for water tax calculation is as follows:

$$N_{\text{full}} = \left(\frac{k_1}{n_1} + \frac{k_2}{n_2} + \frac{k_3}{n_3} + \frac{\lg(\alpha)}{\lg(\alpha_{\max})} + \frac{T - C_r}{T} + 1 \right) \cdot N_{\min},$$

k_1	The category of water user;
k_2	The of category groundwater reserves;
k_3	The category of complexity of the geological structure and hydrogeological conditions of the resources;
n_1, n_2, n_3	Scale factors;
α	The equity ratio (use factor);
C_r	The cost of ready-to-use groundwater;
T	Average regional water rate;
$N_{\min}$	Minimum starting water tax rate.