**Artificial systems evolutionary learning**

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**Abstract** - The idea and technology of artificial systems evolutionary learning is developed. The concept of intellect is dissociated from physical realization of thinking processes. New understanding of learning process discrecency taking into account the artificial system life cycle limitedness principle is formulated. The two-module concept of artificial system modeling is proposed. It consists of two connected modules which have different properties and life cycle. New concept of B-System is introduced. The artificial systems evolutionary learning task formalization on the base of resource approach is executed. The principles formulated allow to simplify technologically the artificial systems learning processes, to decrease the "artificial system-learning environment” pair connections and interaction factors complexity.

**Keywords:** Intellectual artificial systems, Evolutionary learning, B-System.

1 **Scientific issue analysis and formulation**

The modern evolutionary artificial intelligence techniques are traditionally based on physical laws and known world part organization methods. The scientists concentrate their efforts on researching the physical parts of matter, their connections and transitions. While modelling evolution processes in the variety of aspects, for instance, using cognitive approach [1,2], the researches are grounded on study and modelling the real physical, physiological processes which are in natural systems. The thinking processes concerning the intellectual systems are considered as the possibility to use the knowledge and deductions based on the knowledge for effective and rational system behaviour implementation [3]. Information analysis, systematization, and storing are not detached from system physical platform. There are many theories and techniques for thinking processes in natural systems reproduction [4-6], for example, neurons and neuron systems modelling [7-10]. But full-fledged artificial intelligence creation issue is not solved yet.

For creation the artificial systems with intellectual features the most substantial and problematic are the processes of the intellectual parts learning, specifically control modules [11]. For designing this kind of modules intellectual agents technologies can be used. But for their adaptation in an environment the reinforcement learning technique is considered as the most effective and reliable [12]. It is based on reinforcement learning theory [13] which can be considered as adaptive behavior theory development. But there are many reasonable obstacles because of the learning task complexity and multiple criteria existence.

2 **Objectives**

For the further development of artificial intelligence creation task solution methods the new conception and technology for artificial systems evolutionary learning is needed. Also, it is necessary to formulate the principles for artificial systems learning process technological simplification, connections and interaction in "artificial system - learning environment" pair operating factors complexity reduction, and artificial system appropriate model creation.

3 **Artificial systems evolutionary development**

Considering this issue the word "intellectual" is not used deliberately concerning to the systems in general and artificial systems specifically. Any system is considered as intellectual with possible margin states with no intellect (for example, in the beginning and the end of the system's life cycle). And any system is considered as origin independent; natural systems (NS) are different from artificial systems only with author (creator) attribute.

Looking rigorously on natural systems, especially systems in evolutionary development, one can notice some common principles: development is where some division and tension because of incompleteness (imperfection) exist; the systems without indivisibility, self-sufficiency, functional completeness evolve.

So, there are two most important postulates:

1. Evolutionary development is possible only with interaction.
2. Interaction is possible only with incomplete system form.

Further, with more attentive world consideration (at least, of human perception perspective) it is seen that any property has its opposition. So, one can guess that the world is based on binary organization, and the matter is only in detalization degree. (For example, there is no discussion that OS Windows is a set of binary codes in its foundation). And
almost always the world can be decomposed to some binary (or couple) component system. The components can be any characteristics, fact, concepts, properties, parts etc. These interesting facts facilitate view that binary principle with algorithmic approaches can be used for artificial evolution description. In this case a vast and very interesting research field is being opened.

But for the beginning let's consider one aspect development. Let's take any intellectual system binary model a artificial evolution basement. Let's consider any intellectual system as $B$-System [14] with carrier and intellectual part separated.

Let's consider the classical spiral evolutionary development idea (figure 1.a). We understand the world change as going from simple to complex and this reflects evolution spiral. Evolution spiral shows world structure complication the most complete way but isn't a definite mirror for direction (technologies) and development linearity (an individual, some intellectual object evolution linearity). An artificial system development is a non-linear process. While developing a system can move step by step on evolution spiral (figure 1.b) but also can move back to some state for repeated study. If intellectual part is saved in this process there is almost eternal artificial intelligence development process.

![Figure 1. An artificial system evolutionary development.](image)

Then it's necessary to explain our understanding of the world as a discrete system. The continuity and discrecity concepts are relative and subjective. So, defining the process as continuous or discrete is relative and depends on the observer. One more important factor influencing artificial systems development process is understanding the aggregativeness of knowledge and skills gained during learning.

So, the following artificial systems evolution main features can be selected: discrecity, aggregativeness, and non-linearity.

Let's consider an artificial system development in more detail. Let's accept that artificial system development is possible only as a result of learning or self-learning. The main challenge for effective learning organization is the complexity of the correct statement of learning task.

There is evident correlation between the time needed for the system learning necessary for its stable state and system complexity on the other hand. The more complex systems need more time for learning than simpler systems. Besides, domain also influences learning time specifically the functions the artificial system must execute after learning. There is no sense to consider learning out of functions the system must implement context. The learning task can be considered only in the context of functions, which the system under learning must be able to run, set limitations.

Taking into account that we have not the abstract learning task without any limitations there is a challenge in formulating the learning objective and criteria system creation (the criteria must confirm learning effectiveness). Besides, it is necessary to take into account that so-called self-learning systems are senseless and can be dangerous if learning is not under control of external environment or learning subject.

4 Artificial systems evolutionary learning subjects

There are three parts of artificial systems learning process (figure 2): object, subject, and learning environment. A learning object is an artificial system (AS) which has to study, specifically gain some knowledge and some set of skills. A subject is a system author (A). It's not possible to set objectives and initiate the learning process itself without understanding the author participation and functions. Of course, the author may have a complex structure, be a separate individual or a union, both natural or artificial, what is not so important.

The third part of the process under consideration is learning environment (C). Depending on author and learning environment correlation there are three different in foundation types of an artificial system learning organization
(figure 1). Case a) in figure 1 demonstrates the situation where the learning environment is detached from the author. Case b) in figure 1 demonstrates the situation where learning environment includes the author in whole or partially. Case c) in figure 1 presents the situation where the author is identical to learning environment, actually, the learning environment is the author. The last case matches artificial system self-learning.

Figure 2. Artificial system learning organization types: a) – exterior independent author; b) – author as learning environment type; c) – author is identical to learning environment.

5 Evolutionary learning concept

Let's consider in more detail the artificial systems evolutionary learning idea. The modern artificial systems learning methods are various but usually connected with physical characteristics, structure, and learning object and its environment properties. Let's abstract from technical platform and specific artificial system implementation. For making the task simpler let's ignore the inner structure, specific design at the first phase. The task is to describe artificial systems learning technology as an abstraction.

Let's formulate the conception of artificial systems evolutionary learning [15]. The conception is based on the following principles:

1. Learning limitedness.
2. Life cycle finiteness.
3. Learning iteration-hierarchical structurization.
4. Reboot availability.
5. Evolutionary system life cycle specificity.

5.1 Learning limitedness

For limited in time life cycle the system can learn some limited functions set and acquire some limited knowledge. Looking at the natural world we can deduce that there is no universal intellectual system. Every intellectual system has consciousness of some level and can perform some limited functions set. The life cycle of any system is limited and finite. Certainly, during some finite life cycle an artificial system can learn some limited functions set and acquire some limited knowledge. So, it is reasonable to consider increasing an artificial system life cycle making it conditionally infinite.

5.2 Life cycle finiteness

It's not possible to create a system with one infinite life cycle. So, conditionally infinite existence cannot be provided on the base of limited physical reality. Let's accept apriori that for one artificial system existence life cycle it can learn some limited set of functions and skills. Then for learning proceeding the system must get new data and task – the new set of functions to master. So, artificial system learning task comes to interactive learning process creation and the process goes on different hierarchical levels of functioning taking into account the necessity to preserve the part of knowledge and ability to accomplish some functions while going to a new hierarchical level. In this process the system also loses some features and capabilities (technological interface functions) which are not necessary at the next level but were used before to get knowledge and skills and gets some new features and capabilities (technological functions) and initial data allowing to operate new skills in new environment.

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5.3 Learning process iteration-hierarchical structurization

Taking into account mentioned above let's give the learning process complexity simplification. System evolutionary learning process (figure 3) is divided into some hierarchical iteration processes (stages). At the stages some limited learning will be. It will be connected with some concrete environment physical parameters and limited learning tasks. It will cause the finiteness of system life cycle at the current iteration-hierarchical level.

\[ P_{i+1} = F (S_i, T_i) \]

Прич.3. Evolutionary learning stage number i

5.4 "Rebooting" mechanism

Let's introduce "reboot" mechanism concept [15]. After the current system life cycle finish system preparation and transition to the next evolutionary learning stage is provided. During that learning results are saved, the knowledge gained are aggregated, the structure and volume of knowledge gained are optimized, learning results are analyzed for matching the objectives set, the decision of transition to the next learning level (with the possibility to interactively model the level) is made, learning and forming the current technologies of adaptation to the new physical environment tasks are set.

5.5 Artificial system life cycle

Let's accept the following chain as a life cycle:

- initialization (creation) – learning – end(destruction) – rebooting

During first initialization procedure (figure 3) the first evolutionary stage modeling is executed, the learning tasks are defined, the current technologies of adaptation to physical environment are formed. Then learning process is run; in general case the i number learning evolutionary stage \((E_i)\) is executed. At this stage the technologies of reinforcement learning are quite acceptable [12]. After the current evolutionary learning stage number i \((E_i)\) three main "reboot" mechanism procedures should be executed:

1. Saving the artificial system learning results \((S_i)\) – optimization and safety of data received as the learning results in form independent on the environment and physical form.

2. Ignoring non-necessary technical data and service functions \((T_i)\) which were used for the system adaptation to the concrete physical realization and concrete tasks of the concrete learning stage.

3. Analysis \((A_i)\) that is the assessment of matching the learning results to the objectives set, making decision on moving to the next learning stage with interactive modeling possibility, setting new learning tasks, and forming the current technologies of adaptation to the new physical environment.

It's worth noting that both new \((i+1)\) and current \((i)\) evolutionary stage can be selected as the next level (the last is equal to the repeated learning). In a general case an artificial system learning next stage any hierarchical level can be selected.

5.6 System modularity

Let's create an artificial system model considering the evolutionary learning technologies mentioned above. The artificial system is divided into two components. One component includes the intellectual part and is persisted as long as necessary. The other component must be flexible enough and provide system adaptation the environment being changed. This component is not always stable and often is variable, with short existence time. The evolutionary learning system model is represented in two significantly different modules: intellectual module and environment adaptation module (figure 4).

Прич.4. An artificial system module structure.

Intellectual module (IM) is considered as a constant component and is the gist of the system, and actually we can consider it as the system itself. Its' existence time is unlimited. Adaptation module (AM) is a variable component
and provides intellectual module functioning in the current physical conditions. This module must ensure the intellectual part adaptation to the environment current conditions, to the current learning tasks, and artificial system knowledge acquisition stages. Actually, this module is the interface between the intellect and the environment and provides the intellectual module functioning in concrete physical realities. Going through evolutionary stages the adaptation module persistence is not stipulated.

![Diagram of B-System adaptation mechanism to new environment physical parameters](image)

This view on an artificial system provides systems adaptability to new environment physical parameters (figure 6) in time of transition to the new iteration evolutionary stage preserving the intellectual part. So, it allows to provide evolution process beginning from the elementary levels and to provide knowledge accumulation. It is evident that in this view on a system non-linear evolutionary process can be easily realized.

![Diagram of B-System in the process of adaptation to the new environment parameters taking into account the evolution processes non-linearity](image)
6 Learning task formalization. Resource approach

Let's make artificial system learning task formalization at iteration-hierarchical learning process evolution stage number $i$.

At initialization time at evolution stage $i$ the learning tasks discretization is executed. The finite set of functions which the artificial system must master is determined. So, at the evolutionary stage $i$ the artificial system must implement $M$ learning processes. Some set of resources $R'$ is given to the artificial system for executing every process at evolutionary learning stage $i$:

$$R' = \sum_{k=1}^{M} r'_k$$

For one $k$ number process execution it is necessary to master some limited resource set $N'_k$. It is possible to define the executed learning process condition using full mastering the existing resource $R'$ condition at $i$ evolutionary learning stage:

$$\sum_{k=1}^{M} \sum_{j=1}^{N'_k} r'_k N'_j = R'$$

where $r'_k$ - the amount of $j$ resource processed with $k$ learning process.

The objective function of learning at $i$ evolutionary stage can be represented as:

$$F^i = \sum_{k=1}^{M} \sum_{j=1}^{N'_k} z'_k N'_j + \sum_{k=1}^{M} \phi'_k(N'_k, N'^i)$$

where $z'_k$ - expenditures of resource $j$ in process $k$ at artificial system learning evolutionary stage $i$.

It's evident that $N'_k$ is always less than $N'^i_k$ - the maximum of possible number of an artificial system learning processes realized, that is resources consumed at evolutionary stage $i$.

$\phi'_k$ is a fine function for the executed learning processes number deviation from maximal number of executed learning processes at evolutionary stage $i$.

So, an artificial system learning task at evolutionary stage $i$ can be formulated the following way:

to minimize the objective function (3) observing the limitation (2).

7 Conclusion

Artificial systems learning organization on the evolutionary techniques base can increase learning effectiveness. The idea and technology of artificial systems evolutionary learning is developed. New understanding of learning process discrecity taking into account the artificial system life cycle limitedness principle is formulated. The two-module concept of artificial system modeling is proposed. It consists of two connected modules which have different properties and life cycle. New concept of B-System is introduced. The artificial systems evolutionary learning task formalization on the base of resource approach is executed. The principles formulated allow to simplify technologically the artificial systems learning processes, to decrease the "artificial system-learning environment" pair connections and interaction factors complexity. It allows to develop artificial intellectual systems evolutionary learning building and organization methods in future.

8 References


