

# Automatic origin of a language in AAC neuron-like systems

A.A. Zhdanov, [alexander.zhdanov@ispras.ru](mailto:alexander.zhdanov@ispras.ru)  
A.M. Kondukov, [alekond@yandex.ru](mailto:alekond@yandex.ru)  
T.S. Naumkina, [tomat@7ka.mipt.ru](mailto:tomat@7ka.mipt.ru)  
O.A. Dmitrenko, [oply\\_ly@mail.ru](mailto:oply_ly@mail.ru)

Institute for System Programming RAS  
[www.ispras.ru](http://www.ispras.ru), [www.aac-lab.com](http://www.aac-lab.com)

## Abstract

The paper present our first results of simulation of a simple language origin in neuron-like Autonomous Adaptive Control (AAC) system. The language origin is based on properties of neurons allow them associate different patterns. If one pattern is pattern of a real object and other one is the pattern of a verbal object the neuron can associate them. The set of pattern-identifiers and special linguistic action forms a language and allows to control the object from outside or to use it by object itself for thinking.

## 1. Introduction

Despite the fact that language is in the focus of attention of human culture always and that a lot of studies concern to this phenomenon the origin of language is not frequent issue of cybernetic researches. However, we are convinced that such language aspects as its origin processes and using in natural controlled objects – living creations are very important and have to be investigated and simulated in computer programs. Let us discuss some results of our attempts to investigate the language origin mechanism in neuron-like structures and results of computer simulation of the phenomenon by means of our model of nervous system named the “Autonomous Adaptive Control” (AAC) system [1].

## 2. Autonomous Adaptive Control (AAC) Method

In our research we deal with the simulation of language effects that appear during functioning process of a model of nervous system. We have used our neuron-like AAC system as a model of nervous system. Under the AAC system macro description the follows units are consider (Fig 1): *controlled object* (CO) – simulated organism; *control system* (CS) – simulated nervous system, which is subsystem of CO; *environment* where the CO is situated; *the system* – CS, CO and environments as a whole; *sources* – the beginnings of any influences in the system (shown as white circles); *sinks* – the points where physical and informational processes are disappear (black circles).

We accepted following initial conditions, which are specific for nervous systems:

1. *Autonomy condition* requires treating the CS as a subsystem of CO, which independently controls the CO and dig up new knowledge that is necessary for control. Fig. 1 shows CS, CO and environment as included each to others sets of units and processes, and possible routes of information and influences starting in sources and finishing in sinks. The system presentation allows us to see that CS controls not only CO, but also the system “Environment – CO - CS” at whole. And at the same time the sources bring for CS some random influences and sinks consume a part of such influences that is why a random constituents in system functioning process appear.

2. *Discreteness condition* takes into account the fact that nervous system structure is discrete in some respects: neurons, nerve fibers, nervous pulses, sensors, executors and so on. Furthermore nervous system has continuous processes that can be useful for NP-complete tasks solution.

3. *Maximum initial adaptability condition* reflects the necessity of adaptation of any biological species to its ancestor’s typical living conditions as a result of the evolution. This condition requires maximal using of a priori information for the most complete initial adaptation as CO as CS for living conditions.

4. *Minimum initial knowledge condition* defines the fact that newborn’s nervous system has the minimum of initial knowledge and has to accumulate information, which is necessary for control process during its life.

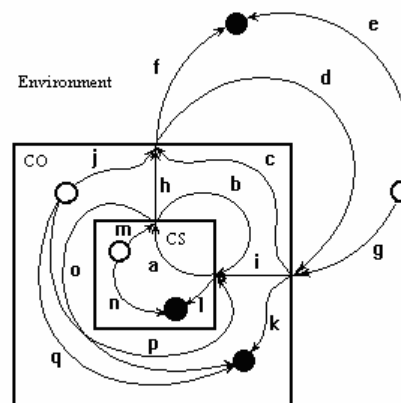


Fig. 1 System “Environment – CO - CS”

We suppose that any nervous system has two most important goal functions:

- the organism surviving* and
- aspiring to accumulation of new knowledge.*

All others goal functions are subordinated to these main goal functions and their derivatives.

As it forcedly follows the above conditions and goal functions the SC must solve certain consistent tasks, namely:

- CS simply must find nonrandom regular information patterns in input data entered from sensors because the patterns reflect nonrandom phenomena and processes in CO and environment. This is the *pattern formation problem*. In mathematics it is similar to the problem of automatic classification, clusterization. Formed patterns are stored in “Pattern Memory”;
- CS must recognize the formed patterns in the current input information/ It is the *pattern recognition problem*;
- CS must find special patterns – *knowledge that* reflects nonrandom cause-effect relations of system events. CS is in need of the knowledge for control that is why CS stores them in “knowledge base” in some special aggregated structures. This is the *knowledge acquisition and representation problem*;

- CS must solve the problem of *inference of new knowledge* from the knowledge, which already stored in the “knowledge base”;

- Emotion subsystem of the CS has to estimate emotional appraisals for the formed patterns, to memorize them and to calculate integrated emotional evaluation for current state of the controlled object – *emotion simulating problem*;

- Each time moment the CS has to do decision making taking into consideration the above goal functions (survival and knowledge accumulation), the “Memory of Patterns”, the “Knowledge Base” and others memory divisions, and on base of recognized patterns of current conditions – *multilevel hierarchical control problem*.

AAC system structure and composition are presented in Fig. 2. From viewpoint of computer sciences the AAC system as a conceptual nervous system model is a self-learning recognition-control complex.

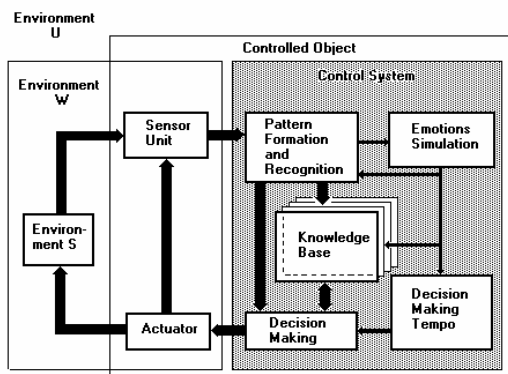


Fig. 2. The functional scheme of the System, containing the Autonomous Adaptive Control System (AAC), the Controlled Object and three kinds of Environment. The CS controls the Environment signed W.

### 3. Neuron-like implementation of AAC system

Separate subsystem of AAC system can be implemented with various appropriate methods of pattern recognition, knowledge representation and so on. But neuron-like realization of AAC CS has especial interest because it closely connected with biology. Special models of neurons had been elaborated for AAC system that corresponded to our conception about functioning of biological neuron. The basic principle of this neuron model is given below. We are convinced that biological neuron is self-learning system of automatic classification. The synapses is known to have a property of plasticity that force a faster growth of only group of synapses that take part in transportation of correlated signals. This characteristic is a key moment that allows the neuron to find the correlated events in system, including non-random cause-effect occurrence. The models of neuron developed for AAC system [2] accomplish exactly this property in the first place. Even the most simple neuron model (Fig. 3), is able to find out simple law consisting that more than  $M$ ,  $M=const$ , of individual input signals come simultaneously, allows to build a lot of useful application adaptive control systems.

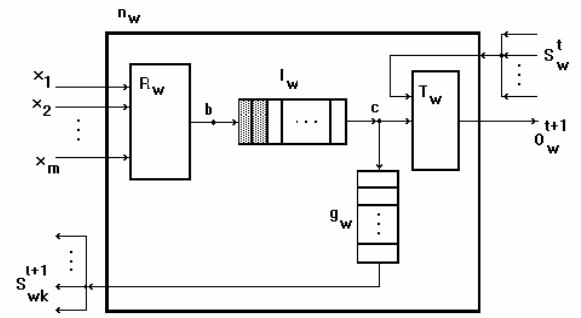


Fig. 3. The neuron model is able to generate language effects.

By means of the bloc  $R_w$  the neuron test hypothesis about composition and structure of sought pattern. In the general case the hypothesis may have any complexity but we used rule that may be implemented by biological neuron. For example it is the rule of logic threshold AND. If input vector satisfies the given hypothesis about structure then the neuron tests a statistical hypothesis by means of block  $l_w$  that examines whether the vector satisfies an established statistical criterion. At the same time a statistics of appearances of such vector is calculated to determinate whether this event in system is random one or non-random one. If statistical rule is satisfied once then the neuron understands that this vector is non-random one and that it corresponds to some non-random appearance in the system. From this time moment the neuron take up new condition (recognition mode) in which it is be able to recognize given pattern anytime. In recognition mode the bloc  $R_w$  finds out the pattern, bloc  $l_w$  confirms its non-randomness and trigger bloc  $T_w$  switch over and generate output signal  $O_w^{t+1}=1$  for other neurons. The signal informs others neurons that the pattern was recognized. This output signal will exist as long as it will be perceived other neurons or subsystems of CS. Then such neurons send inhibiting signal  $S_w=1$  and trigger is set to zero. This logical expressions describe the functioning of described neuron:

$$O_w^{t+1} = \neg S_w^t \& ((b_w^t \& l_w^t) \vee O_w^t),$$

$$S_{wk}^{t+1} = b_w^t \& l_w^t \& g_w^t.$$

We can construct the irregular neural networks from the neuron model. In the AAC neural network one neuron corresponds to one pattern and learned neurons correspond to set of formed patterns. As it is well known in standard artificial neural networks one pattern corresponds to specific output vector of the network. The important property of the AAC neuron is capability for recognition of patterns under noises. We guess this property is similar to the same property of real neuron. If observed object (prototype) is presented to given neuron by means of a binary vector but the vector contains not all set of binary components, then given neuron all the same has to be able for recognition of the object. Admissibility of prototype distortion (part of missing binary components) is subject to a rule. In this model this rule is formalized in the form of rule R, which is expressed by logic threshold function AND. In this function the threshold  $P$  decreases against number of prototype observations. However the vitally important property of neuron to have “noise immunity” leads to such very important phenomenon of live organisms as language, linguistic communication between organisms and ability of one organism to the thinking.

#### 4. Effect of identification

Let us consider a combination of three neurons (Fig. 4). Let neuron  $n_a$  receives a signal from prototype of something object A and neuron  $n_b$  receives a signal from prototype of object B.

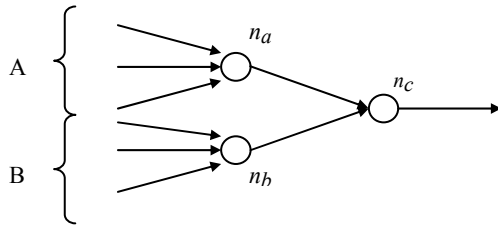


Fig. 4. Construction from 3 neurons. If neuron  $n_c$  is learned it can recognize pattern even when one only of patterns  $O_a$  and  $O_b$  is recognized.

Let neurons  $n_a$  and  $n_b$  had learned already. If these neurons recognize their patterns  $O_a$  and  $O_b$  simultaneously many times then neuron  $n_c$  will be learned too. The threshold of neuron  $n_c$  will fall till 50 % after a time. From this time moment the neuron  $n_c$  can function when one of the object (A or B) is recognized. Thus one object (for example object B) can be used as an identifier of another one (for example object A). This identifier can be helpful when the object does not be available any time. For example the object A is such natural phenomenon as the Sun. A natural creature can recognize the Sun only when the Sun is in the sky. If Sun is not in the sky the creature can not force the neuron  $n_a$  to work and to recognize the pattern of the Sun. But let us there is the neuron  $n_b$ , which is connected with hearing. Let us the neuron can recognize the word "Sun". Let us speak "Sun" each time as the Sun is on the sky. Let us the neuron  $n_c$  became learned and associated the Sun in the sky with the word "Sun". The neuron formed the specific pattern of the Sun in the sky and the word "Sun" as whole. Then we can force the creature to recognize the pattern any time when we speak the word "Sun". For example in midnight when the Sun is not in the sky. If the creature had associated some actions with the Sun then it will be perform these actions if it hears the word "Sun". So we obtain the tool for control the creature. And if the creature can pronounce word "Sun" itself then it will hear the word itself and recognize the pattern of Sun. It is one only natural way to influence on the neuron  $n_c$  without surgery.

Let we have a set of objects that are available at any time, for example set of sounds, gestures or graphical signs. Then let us these objects became identifiers for set of other real object. This set of identifiers is a part of language that provides process of information reception. If at the same time the CO can make something that stimulate object-identification of other CO or itself then these actions provide a "active" part of language, i.e. process of transmission of verbal information.

The set of patterns - identifiers and linguistic actions directed on their call, in essence makes a lexical basis for "language". Language, as the system of identifiers, is formed during learning process, when real objects associate with objects - identifiers. During the process some neurons learn and their thresholds decrease.

#### 5. Language

Control cycle ...a-h-d-i-a... (Fig.1) represents temporal cycled sequence of recognizable patterns shown at Fig. 5. Several similar sequences are working simultaneously.

Since each of these patterns is implemented by means of neurons there is a possibility to establish a correspondence between each of the patterns and an identifier. In order to do that it is necessary to demonstrate such pattern-identifier at the same time with that pattern, which the "teacher" wants to associate it with. Such identifiers allow us to see some parts of speech: real objects pattern-identifiers are nouns, action patterns-identifiers are verbs, emotional appraisals pattern-identifiers are adverbs ("badly", "well", and so on).

The ways of using of such identifiers are rather various. For example, we can cultivate pattern identifier for negative emotions (to do this, having said "bad" we should make something that stimulate negative emotions), and then use this identifier for different inhibitions. In other words, if CS is going to perform some action, that we do not prefer, we should say "bad" and the knowledge base will store the fact that that action stimulate word "bad" pattern, what has negative emotional estimation.

#### 6. Language types

Let us return to the Fig.1. As said above we can have linguistic objects observed by CS via its sensors and linguistic actions on CS outputs. But looking at the figure you can see that they both may be related as with cycle ...a-h-d-i-a... that passes through CS, actuators, environment and sensor unit as with the cycle a-b- that passes inside CO.

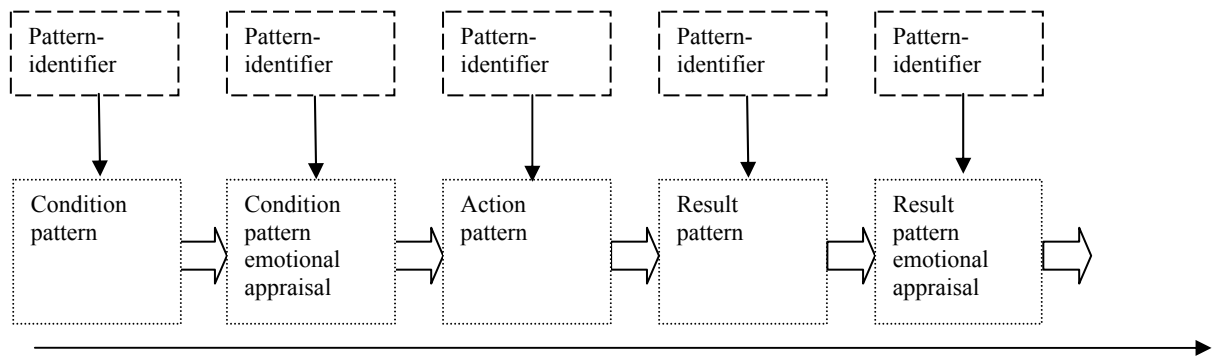


Fig. 5. Consequence of events under control process.

Time

If linguistic objects and actions belong to the 1<sup>st</sup> cycle, i.e. passes through environment then such language we call *external language*. The main ways to use external language is communication with another objects located in the environment and understanding this language and for speaking with itself.

If linguistic objects and actions belong to the 2<sup>nd</sup> cycle then we deal with *internal language* used by CO only for communicating with itself.

We suppose that external language must be the first to form. Its “informational power” depends on objects variety, which the creature may use as identifiers and energy consumption required for manipulating these objects. So waving of heavy horns or hoofs and three kinds of moos can hardly be a language for cow. It is possible that larynx being able to utter many sounds and finger’s agility play a main part in forming human language and intelligence. Do not forget about well-known monkeys (Koko and others) some of which are successfully learned to speak with people by means gesture language for deaf-mute.

## 7. Modeling language phenomenon

We began practice works of language effects modeling recently. These works were realized with program model of the mobile robot controlling by AAC system. Robot was named *Gnome 8* [3]. The robot has a circular shape in the plane. There are visual and tactile sensors on the face side (Fig. 5). Each visual sensor has its own field of vision. Robot feels a need of three resources. It can fill up the resource by approach of its source. Robot is controlled by three-level AAC system. On the highest level control system is learning to choose aim, on the middle level – to find a strategy of aim approach, on the lowest level – to drive without collisions with the obstacles.

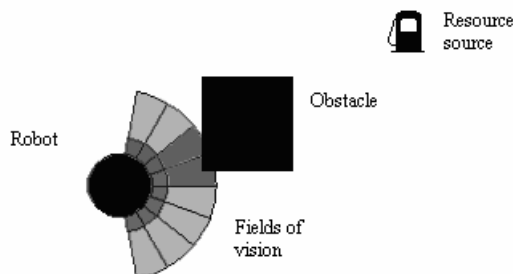


Fig. 6. Robot “Gnome 8”

### 7.1 Modeling identifier of the condition pattern

We added some sensors for modeling of the language effects. These sensors receive sound signals, which are used for creating of the identifier patterns. We added also some neurons in formation and recognition subsystem. So it can recognize three sound-identifiers, which mean “obstacle on the right”, “obstacle on the left” and “obstacle on the center” and create corresponding associative patterns. Robot was trained to recognize this “words”. Then it was set in position where there weren’t obstacles around. When one of these “words” was pronounced mobile robot recognized this word as the pattern of the obstacle. So robot responded to the virtual

obstacle. In that way the language patterns of the obstacles were formed.

In the next experiment we added word-identifiers the semantics of which were in the following: “not enough of the 1st resource”, “not enough of the 2nd resource” and “not enough of the 3rd resource”. And in this case training was successful too and robot trained to react to “words” as to real objects.

### 7.2. Modeling of the multi-step reasoning

At present we are simulating “talk” robot to itself. It opens the way to multi-step “reasoning” such as: “if I do this in such way then I’ll get *A* result and so I can do *B* and then I’ll do *C*” and so on. As were written above the “talk” robot to itself may occur in two ways: with external or with internal languages (“aloud” or “to itself”). For the present time we consider only external language because it is simpler. There were two algorithms that we consider:

1. CO recognizes pattern  $O_i$ , pronounces word  $W_j$  that corresponds to the *j*-th action, pronounces word  $W_k$  that corresponds to pattern  $O_k$  (result pattern) then CO hears itself, recognizes word  $W_k$  as a condition pattern, again pronounces word that corresponds to some action and so on. Thus, the line of reasoning looks as “action-pattern-action-pattern-...” In natural language it corresponds to construction: “If I do ... then ... and then if I do ... then ...”.

2. CO recognizes pattern  $O_i$  then makes some operations and “says” word  $W_k$  that corresponds to result pattern  $O_k$ , then “hears” itself and so on. In this case the line of reasoning looks as “pattern- pattern-pattern-...” In natural language it corresponds to construction: “Now I have ... , I can do ... so that get ... later I’ll be able to get ...” and so on.

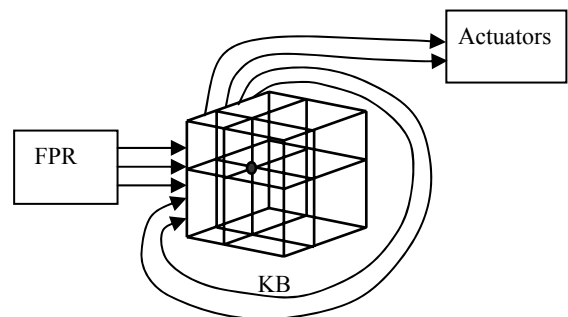


Fig. 7. Multistep reasoning basic circuit

On the next stage we are going to simulate language relations of two or more controlled objects using the external language.

## 8. Conclusion

We showed a possible mechanism of language origin in the neuron-like nervous system model - system of Autonomous Adaptive Control (AAC). The process is based on some specific properties of models of biological neuron. The main property of neuron is its ability to association of different patterns. In the case if one pattern is the pattern of a real object and another one is the pattern of a word or other verbal sign we can obtain verbal identifiers of real objects and then use them for control.

Moreover the language as a system of identifiers allows to different controlled objects communicate each other and allows to an individual controlled object talk to itself for thinking under multistep decision making.

## 9. References

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