MODEL CONSTRUCTION AND RESEARCH USING SYSTEM COMPOSITIONAL APPROACH ON NATURAL HIERARCHICAL NEURAL NETWORKS. DEVELOPMENT OF COMPUTER TOOLBOX

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Abstract: System compositional approach to model construction and research of informational processes, which take place in biological hierarchical neural networks, is being discussed. A computer toolbox has been successfully developed for solution of tasks from this scientific sphere. A series of computational experiments investigating the work of this toolbox on olfactory bulb model has been carried out. The well-known psycho-physical phenomena have been reproduced in experiments.

Keywords: system compositional approach, mathematical and computer modelling, elementary sensorium, hierarchical neural networks, computer toolbox, olfactory bulb.

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Introduction

Physics, mathematics and modern computer science are universally recognized instruments for research of complex processes and phenomena of the real world. In addition to traditional research domains of these sciences more and more disciplines are being involved into their sphere of interest. In scientific literature dedicated to interdisciplinary exploration the expression “mathematical and/or computer model” occupies the most prominent place.

This paper is dedicated to the topic of mathematical and computer modelling and research of cognitive processes in the brain.

Recently a lot of scientific researches were conducted, where those phenomena and processes are investigated, which have never been involved into the sphere of physico-mathematical and computer applications. The tendency to formalization appears especially in those knowledge domains, where a direct experiment giving the possibility to collect reasonably complete and objective information about the reality under research is impossible in practise. It is commonly known that neuron sciences for instance occupy one of the leading places in modern biology according to the number of physicians, mathematicians and computer science specialists involved competing with molecular biology, genetics, and biotechnologies. According to the complexity of appearing interdisciplinary problems neuro-sciences even leave others behind.

Fast accumulation of enormous amount of experimental data, especially in the last decades of twentieth century and the beginning of the new century has prepared a foundation for trying to develop (on a basis of modern imaginations and possibilities) a new conception concerning the natural mechanisms of recognition, memory and purposeful thinking. Also alternative approaches exist, which are dictated by queries of both fundamental and modern practical medicine and by search of new non-traditional ways of creation of “intellectual” technics.

The idea, that theoretical constructions can appear only on a basis of wide experimental material reflecting the subject under investigation completely, is still popular in the scientific society. However, the history of natural science does not prove this conception on the one hand, and numerous examples urge us to think, that the motivating stimulus of developing and creating a new conception is usually a limited set of fundamental facts on the other hand. Though, the experiment gives food for theoretical constructions no any doubt and serves as a foundation for a future theory. It is worth to emphasize, that similarly to the theory, which is supported with experimental facts, the experiment gives useful information only if it is carrying out according to a specific theoretical conception.

In this paper we discuss questions concerning with mathematical modelling and research of cognitive processes inside the human brain. For this matter computer toolbox was introduced and discussed. While being created first of all it was oriented to networks with complex architecture, namely non-linear hierarchical neural networks of interacting neurons and neuron ensembles (which are made of simpler neural networks in turn) with taking into account energy dissipation as a matter of fact. The last circumstance be known let us take into account and model very important aspects connected with self-organization. It is worth to emphasize we will research and model multilevel hierarchical neural networks with forward (ascending, aggregating), backward (descending, decomposition), and cyclic (parallel, positive and negative) connections. At the same time we will operate with so-called basic structures, which probably the complex brain-like structures (e.g. memory), generally speaking, of large dimension are constructed from. We hope that developed in cooperation with our colleagues [1,2] approach will help to achieve deeper understanding of human's nature and brain activity. Necessity for research and modelling of such neural networks with complex architecture appears when solving the tasks of multilevel information processing inside the brain and for computer modelling, complex behaviour, decision making, etc.

At the present moment it ought to be said, that existing experimental data and conceptions concerning the neuronal activity characteristics and interaction principles have not yet led to complete understanding of such information processing procedures as memorization, recognition, thinking, etc. inside the brain. The mechanisms concerning the functioning of attention, distinction of unconscious and conscious psychical processes, influence of emotions, etc. are still not explained.

Mathematical Model of Elementary Sensorium: Basic Notions

By the *neural model* of sensorium we further imply a model, consisting of neurons and synapses, which incorporate a complex hierarchical network structure (generally speaking, of high dimensionality) of interacting neurons and neuronal ensembles. *Synapse* is treated as a connection of two *neurons*. Neurons and synapses are treated atomic.

Neurons are connected between each other using synapses. In turn, synapses and neurons are connected with pre- and postsynaptic *membranes*. If a pathway of a signal transmission is from the neuron to synapse, then the membrane is called *presynaptic*, if a signal is transmitted in reverse direction, then the membrane is called *postsynaptic.*

Let's regard the representation of sensory (non-verbal) information inside the brain. Cnsider, taking into account [3], that:

1. there is a model of outside world in the brain (neuronal engram);
2. information about sensory environment is transmitted into the brain being encoded by sensory systems;
3. the model of sensory environment is represented as sensory systems with their supermodal level (neuronal model);
4. basic units of nervous system, neurons, correspond to the objects of outside environment;
5. objects of sensory environment effect on neuronal model;
6. changes of the model – "informational processes in the sensory part of brain"

Main Basic Elements and Compositions of the Model of Elementary Sensorium

Let's pay more attention to the discussion of the main basic notions and elements as well as of the compositions of the model of elementary sensorium.

The model consists of *synaptic levels* (SL). There are *symbol* and *quasi-symbol neurons* (SN and QSN) on every synaptic level, which form *symbol* and *quasi-symbol fields* respectively. The main difference between symbol and quasi-symbol neurons is in what functions they perform and how their activity is interpreted, though both have a similar structure. Symbol neurons correspond to particular objects as a whole. Those quasi-symbol neurons, which are connected by positive backward links with some symbol neuron, represent properties of the single object, which the symbol neuron corresponds to. The higher level of hierarchy they are located on, the more complex object (and more complex properties of former) they represent [2]. Let's define symbol and quasi-symbol neurons in aggregate be *principal*.

Let's define symbol neurons SL-0 as *receptors*. Both symbol and quasi-symbol neurons can exist on every level. The only exception from this rule is SL-0 – the level of receptor neurons. This one does not contain quasi-symbol neurons. Receptor neurons correspond to indecomposable elementary objects, which the system of generators of higher level SL symbol neurons are defined by. Receptors are symbol neurons themselves.

Let us distinguish quasi-symbol neurons of SL-1 separately. We define them be quasi-receptor neurons as long as they duplicate receptor neurons [2]. The set of quasi-receptor neurons are denoted as *quasi-receptor field*.

Symbol and quasi-symbol neurons in the model are organized into the *basic structures* (BS), which form a hierarchical neural network. The notion of basic structure is introduced based on neuron structures defined in [2-3]. Every basic structure is defined by certain symbol neuron located, for determinacy, on SL-i. This neuron is termed *determinative* for BS. BS consists of the determinative neuron N itself, the set of quasi-symbol neurons K_i on SL-i, which have positive feedforward and feedback with SN N, the set of symbol neurons S_{i-1} from SL- i-1, whose axons converge to the determinative neuron of BS. All synapses and inserted neurons, which a connection between N and K_i, N and S_{i-1}, K_i and S_{i-1} is realized by, belong to the basic structure also. Aforementioned basic structure is defined as BS corresponding to the neuron N.

it is significant , that the neural network, which is not provided with mechanisms for new BS creation, cannot be trained to recognize new objects. It is capable to recognize only those objects, which corresponded symbol neurons exist for.

Further the principal parts of basic structure components are defined.

Let's consider the i-th synaptic level. A *symbol group* corresponds to each SN. Let's define the symbol group of the determinative neuron of the i-th synaptic level as a part of corresponding BS, which consists of quasi-symbol neurons, synapses, inserted neurons and synapses, which belong to the i-th synaptic level and mediate connections between the symbol neuron and quasi-symbol neurons corresponded to it. It is significant to note, that the connections of the symbol neuron with other ones in the same SL are not included here.

Let us define a notion of *converging group* for the symbol neuron N from SL-i. This group is formed with symbol neurons of SL- i-1, which alter, most often indirectly via synapses and inserted neurons, the state of N (i.e. alter its membrane potential), and also with all intermediate neurons and synapses, i.e. neurons whose output signals are input signals for N. Note, that even though this influence can be mediated with other neurons, it cannot be mediated with other principal neurons.

A notion of type of the neuron and single-type neurons is very important. Informally, the neurons are single-type neurons if they excite to the same quality input signals. Let's introduce formal notions. Let's define a notion of *type of neuron* for symbol neurons. On SL-0 the types of neurons are given as initial characteristics of the neural network and are the elements of some set of elementary types. This set is denoted as RT. For SL-i ($i \geq 1$) the notion is given inductively. Let's consider the symbol neuron N on SL-i. Let the symbol neurons from the converging group of neuron N have types $t_1, t_2,\ldots,t_n$. Then the type of neuron N is $\{t_1 \cup t_2 \cup \ldots \cup t_n\}$ by definition. The type of quasi-symbol neuron is defined by the types of symbol neurons, whose output signals are input signals for the considered quasi-symbol neuron. It is significant, that in the model the types of these neurons coincide. if types of two neurons coincide, then they are *single-type neurons*,. Obviously the *single-type relation of neurons* is equivalence relation.

Based on the paper [4] as well as on papers [1,2] for more precise modelling it is worth to take into account, that before the impulses of single-type symbol neurons reach the target symbol neuron on the next level, the initial signals could undergo some modifications, while passing through the inserted neurons and the row of synapses. At the same time, the signals from single-type neurons can interact independently on the signals of neurons of other types. As a result a notion of *uniform converging group* is introduced. Its definition is just the same as one of converging group with a bit difference: uniform converging group comprises by those and only those neurons of converging group from SL-i-1, which are single-type neurons. Consequently, for the symbol neuron its converging group is decomposable into a set of uniform converging groups. Note, that there is a particular set of synapses and neurons, which the uniform converging groups interact through. At the same time these neurons and synapses are not contained by any uniform converging group themselves.

A *projective group* of quasi-symbol neuron *N* of SL-*i* is a set of neurons and synapses, which consists of quasi-symbol neuron *N*, single-type symbol neurons from SL-*i*-1, whose outputs are inputs of *N*, and also synapses and inserted neurons which these connections are mediated by.

A *descending group* of quasi-symbol neuron N_k of SL-*i* is formed with neuron N_k itself, all quasi-symbol neurons from SL-*i*-1 accepting the input (possible indirectly) from N_k without intermediate principal neurons, and also all intermediate neurons and synapses (if any). Note, that descending groups appear for neurons on SL-*i* for $i \geq 2$, as long as quasi-symbol neurons appear starting from SL-1.

Horizontal pair of symbol neuron N_s of SL-*i* is a neuron N_s' from SL-*i*, N_s itself, to which a signal is passed to from N_s' without other intermediate principal neurons. All synapses and inserted neurons, through which the signal is passed from N_s' to N_s belong to horizontal pair as well. A notion of *horizontal co-pair* is similar to one of horizontal pair with a single difference: *N* is not a recipient but a source of a signal.

A *horizontal group* of symbol neuron *N* is a union of all its horizontal pairs.

A *horizontal co-group* of symbol neuron *N* is a union of all its horizontal co-pairs.

Basic Properties of Notions Defined for Elementary Sensorium

Taking into account neuro-physiological data [4], particular relations have to be held between uniform converging groups, projective groups and symbol group. Let us define them formally. Consider a symbol neuron N_s is in SL-*i*. Let N_k be a quasi-symbol neuron, which belongs to a symbol group of neuron N_s. By definition for aforementioned notions the following condition hold:

SCP1. Let $n_1, n_2, \ldots, n_p$ be a set S of all symbol neurons, which are included in projective group of quasi-symbol neuron N_k on SL-*i*. Then S is equal to a set of all neurons SL-*i*-1, which belong to a particular uniform converging group of the symbol neuron N_s. At the same time N_k is included into the symbol group of N_s. The inverse assertion holds as well. The set of symbol neurons S of SL-*i*-1 of some uniform converging group N_s coincides with a set of symbol neurons, which such quasi-symbol neuron N_k' exists for, that S is a set of symbol neurons of the projective group N_k', while N_k' itself belongs to the symbol group of N_s. A projective group with a set of symbol neurons *S* and a uniform converging group with a set of symbol neurons *S* on SL-*i*-1 are referred as *corresponding*.

SCP2. Vertebrates have the following feature for some sensory systems, for olfactory system [4] in particular: often in the corresponding uniform converging and projective groups intermediate elements between the set *S* and target symbol and quasi-symbol neurons are equal. The neuron processes, diverging on the output, are different only. Some of them are inputs of the symbol neuron, others – quasi-symbol. Further such corresponding groups are referred as *adjacent*. Note, that inside the olfactory bulb (OB) exactly the adjacent projective and uniform converging groups hold.

Let us specify a property, which links uniform converging and descending groups (SCD1). Let two single-type symbol neurons N_s^1 and N_s^2 of SL-*i*-1 belong to the converging group of the symbol neuron N_s on SL-*i*. These neurons belong to the same projective group of certain quasi-symbol neuron N_k (see SCP1). Let quasi-symbol neurons $N_{k,1}^1, \ldots, N_{k,m}^1$ and $N_{k,1}^2, \ldots, N_{k,n}^2$ (and only they) belong to symbol groups N_s^1 and N_s^2. Then these neurons belong to the descending group of the quasi-symbol neuron N_k. Let us define the part of descending group of neuron N_k, which consists of quasi-symbol neurons $N_{k,1}^1, \ldots, N_{k,m}^1$ and intermediate synapses and neurons, which $N_{k,1}^1, \ldots, N_{k,m}^1$ are connected with N_k by, as *descending symbol subgroup* of the descending group of quasi-symbol neuron N_k corresponding to the symbol neuron N_s. Defined property is a generalization of some results from of paper [4].

Correspondence between Defined Notions of Sensorium and Olfactory Bulb Elements

Let us give a description of the symbol group, which represented in the neural network described in [4]. Tufted cell (TC) represents a symbol neuron. Mitral cells (MC) which correspond to TC represent the quasi-symbol neurons, and signal goes through a granule cell.

Converging and projective groups in the OB cannot be described as a simplest case. Synaptic connections so-called olfactory zones (OZ) are located between receptors (SL-0) and tufted and mitral cells (SL-1), which interact via interglomerular cells. Also inside OZ a pre-synaptic inhibition exists. I.e. integrally the converging groups on SL-1 in OB are much more complex than the simplest case. Former description is a description of the converging group in OB on SL-1 for the tufted cell [4] as well.

In OB the uniform converging groups are strictly expressed – there are tufted cell N_s certain OZ and also all receptor neurons, whose axons are connected with this OZ. There are also some additional connections between various OZ which belong to the converging group N_s – this interaction realized via inter-glomerular cells. Thus, this fact shows additional connections between uniform converging groups which were mentioned above [4].

Regard the horizontal groups and co-groups presented in OB [4]. High order tufted cells influence low order tufted cells via vertical short-axon cells. Thus, higher order tufted cell with some vertical short-axon cell together and synapses between them forms a horizontal pair with tufted cell of lower order, which has synapses with corresponding vertical short-axon cell. In turn tufted cells of lower order form co-pairs with higher order tufted cells. Similarly tufted cells of the same order influence each other via the horizontal short-axon cells [4]. Here also pairs and co-pairs exist, which in turn are parts of groups and co-groups.

The common part of adjacent projective and uniform converging groups is represented in OB by olfactory zones – they represent that common part, which is specified in the definition of adjacent groups [4].

Description of Computer Toolbox for Biological Neural Networks Modelling

The toolbox is a computer programme, input data of it is a neural network and its inputs described in XML language [5]. The input neural network is defined as oriented graph.

Oriented Graph of Neural Network. Vertices and Arcs. The first stage of the neural network construction is specification of vertices. Vertices are intended to define specific points of the model. Under “specific points” we understand locations of the neural network, where some signal transformation, nonlinear as a rule, takes place. During the modelling these locations with sufficient accuracy can be substituted a single point for, i.e. vertex. The examples of specific points are pre-synaptic and post-synaptic membranes, axon hills, etc. The arcs of the graph define the direction of signal transmission. They have such attributes as type, length, and coefficient of signal increase/decrease.

Neurons and Synapses

To specify the network in a more intuitive way the basic types of elements of biological neural network are distinguished. Also using them the method, how to pass signals along the arcs, is specified. In a graph, representing neural network, neurons and synapses represented by its sub-graphs, every arc belongs to only one network element, neuron, or synapse (Fig. 1).

Some vertices can belong to both neuron and synapse simultaneously. In this case vertices model either pre- or postsynaptic membranes. Some vertices in the neural network are input vertices. They correspond to the endings of dendrites of receptor neurons in natural neural networks. For each input vertex the input signal is specified by a set of pairs (instant of time, level of signal).

If the level of signal is needed for a certain instant of time which is not specified in input the signal is calculated as a result of linear interpolation. For all that, the inquired instant of time should be hit between the minimal and maximal instants given in input. All vertices are also output vertices, i.e. it is possible to obtain the level of output signal in any particular instant of time from them.

Designed data structure for vertex description in neural network provides an ability to store the history of signal level in the vertex. it gives ability to analyze the signal changes in the vertex during experiment carrying out. After completion of simulation of the network behaviour the toolbox enables to view the history of every vertex.

Time in the Model. Time in the model is discrete; toolbox enables to define the quantization interval. While simulating the level of signal is recalculated in each point in every quantization instant of time. Conventional time units are used in toolbox.

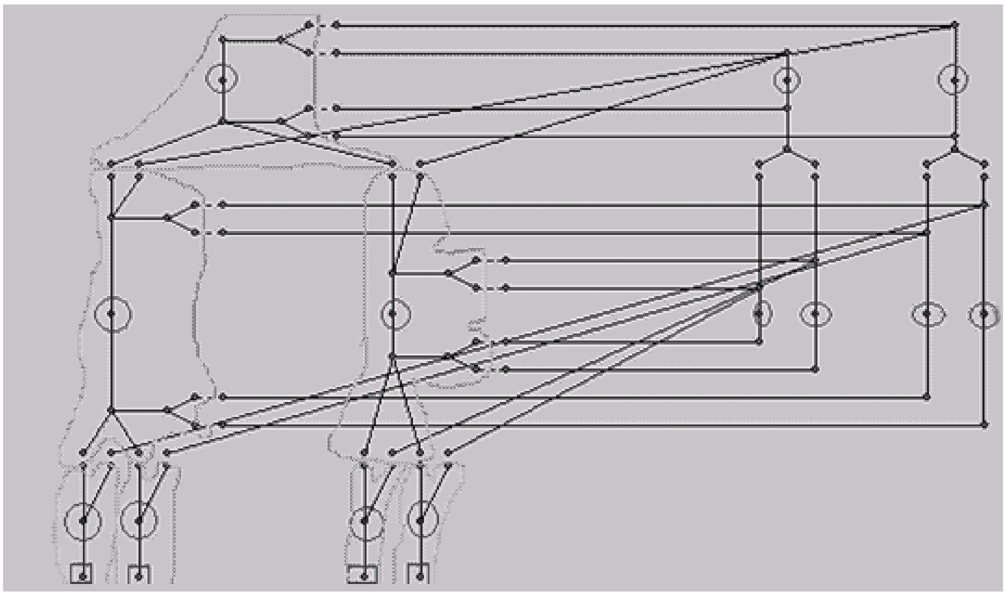

Fig. 1 Example of neural network model in computer toolbox.
For clearness some neurons are rounded with curves. Input vertices are marked with squares. Vertices, where generation of action potential takes place, are marked with circles.

Input Data in the Model. During simulation of aforementioned processes, which take place inside the neural network, there is an ability of real-time visual representation of signal level in any vertex in any quantization instant of time. The more intensive signal level in the vertex in particular instant of time, the bigger circle diameter with a centre in this vertex. Also it is possible to view a diagram of signal level dynamics in any point upon the modelling completion. It is possible to visualize a summary signal level of a particular neuron.

Input Data Representation. The input data is read from XML-document, where the neural network structure is specified. Let us refer to three main elements of this document.

1. *ports* – description of vertices. Each vertex is defined by a title, unique identifier, 2D-coordinates, type (regular vertex or, so-called, generator of action potential (AP), see below). For AP generators the number of vertex (which stores AP sample), a threshold signal level, and coefficients of length and amplitude increment relatively to the sample is defined. Also there is an optional parameter for every vertex – list, which usually defines a signal level of input activity by means of pairs <instant of time, the signal level in a vertex in this instant of time>.

2. *synapses* – description of synapses. The main characteristics of the synapse are its class (chemical or electrical), type and the list of arcs. Every arc is defined by an ordered pair of vertex numbers, length and weight. Note, the notions of length and transmission time of signal in toolbox are synonyms. In the simplest case synapse consists of two vertices, which correspond to pre- and postsynaptic membranes, and one arc, which corresponds to synaptic gap connecting two vertices. There is a possibility to use several arcs to describe synapses more appropriate using facilities presented in toolbox.

3. *neurons* – description of neurons. Each neuron is a particular type of. At this moment there is only one neuron type implemented in toolbox – simple neuron. Similar to synapse, neuron has a list of arcs, the order of which is just the same as the order of arcs in synapses.

Input receptor signals of the neural network are also defined in XML-document, which consists of a list of elements. Each element defines a signal for one of the input vertices as a list of pairs, which specify the level of input signal in a particular instant of time.

Calculation of Signal Values. Each vertex of the network is characterized by certain state in any instant of discrete time $\Delta t \cdot i$, where $i \in [0..n]$, Δt – quantization interval. State is defined by a current signal level of the vertex, the current phase of the action potential and by other parameters depending on the type of the vertex. The state of the network in the current instant of time $\Delta t \cdot (i+1)$ is defined by states of vertices in the network graph.

Let's define a signal processing, which takes place in the vertices. Two types of vertices are used in toolbox: *simple vertices* and *AP generators*. Signal values are defined on inputs of simple vertices in discrete instants of time. Linear spline is constructed based on these points. It can be used in output signal value calculation in any instant of time. AP generators have more complex behaviour. Dependency of the output signal on the input signal is almost the same as in previous item. The important exception, however, is in the following. If signal level reaches the critical level of depolarization and in this instant the vertex is not in state of refractor period, then the action potential with predefined parameters is generated. The type of action potential of the vertex is determined based on the sample taken in [6, pp.27-54], given by a list of pairs of coordinates – dependency of membrane potential on time. In every instant of discrete time in every vertex the values of all adjacent vertices are being corrected, taking into account, which object this vertex belongs to.

Arcs in simple neuron have such characteristics as length and coefficient of signal change, i.e. the signal while passing through the arc is being processed with linear transformation. We stress the simple neuron (not on just any neuron) to emphasize the flexibility and extensibility of toolbox. While time signals in vertices are changed depending on their arc connections with other vertices: $v_j(t) = \sum_{e \in I_j} v_{s(e)}(t - l_e) \cdot c_e$, where generally $v_k(t)$ – the signal value in the vertex *k* in the instant of time *t*, I_j – set of arcs entering the vertex *j*, l_e – the time of signal transmission along the arc *e*, $s(e)$ – the beginning of the arc *e*, c_e - weight coefficient of the arc *e*. Note, that this transformation is inherent to all vertices and is the first transformation, which can be followed by specific transformations related to every particular type of vertex.

In most simple implementations of synapse models the signals are transmitted in a similar way with arcs, but exceptions are regions where mechanisms of plasticity are implemented. Plasticity is implemented by change of the coefficient of signal transmission in synapse according to the following rule:

$$c_{ij}^1 = \begin{cases} c_{ij}^0 \cdot \lambda_{inc}, \ v_j(t + l_{ij}) \geq v_n \\ c_{ij}^0 \cdot \lambda_{dec}, \ v_j(t + l_{ij}) < v_n \end{cases},$$

where c_{ij}^0 – current coefficient of signal conductivity, weight coefficient of a synapse, c_{ij}^1 - new coefficient of signal conductivity while passing along the arc (i, j), $v_j(t + l_{ij})$ – signal level in the vertex *j* in the instant of time $t + l_{ij}$, $\lambda_{inc} \geq 1$ – increment coefficient, $\lambda_{dec} \in (0;1]$ – decrement coefficient of synapse weight, v_n – constant, which specifies a border between the increment and decrement of weight coefficient of a synapse. In order to model more precise complicated synapse type is implemented, where the signal is described by integral transformation:

$v_j(t + l_{ij}) = c_{ij} \int_{t-\Delta t}^{t} v_i(\tau) \cdot e^{-\lambda(t-\tau)} d\tau$, where $v_i(\tau)$ – signal level in the vertex i in the instant at the time τ, $v_j(t + l_{ij})$ – signal level in the vertex *j* at the instant of time $t + l_{ij}$, l_{ij} – time of signal transmission along the arc (i, j), c_{ij} – weight coefficient of an arc, Δt – time interval, which is taken into account during the output signal calculation, $\lambda > 0$ – parameter defining signal decrement. In such synapses signal level on post-synaptic membrane at the instant of time $t + l_{ij}$ depends on the level of signal on pre-synaptic membrane during the period of time $[t - \Delta t, t]$. Thus, while calculating the current state of a particular network vertex not only one previous state is taken into account, but all network states, which occurred during a whole period of time. Consequently, more precise modelling results can be obtained. The summary level of signal of each neuron at the instant of time t is calculated with a sum of signals of all arcs of the neuron, where signal of the arc s_{ij} is calculated like $s_{ij}(t) = \int_0^{l_{ij}} v(\lambda)d\lambda \approx \sum_{k=0}^{[l_{ij}/\Delta l]} v(\Delta l \cdot k)\Delta l$, where Δl – sampling interval in numerical integration, $v(\Delta l \cdot k)$ – the level of signal at the distance $\Delta l \cdot k$ from the beginning of the arc, l_{ij} – length of the arc (i, j).

Verification of Conformity of Toolbox Using Olfactory Bulb Model

In this section the testing of toolbox functionality using olfactory bulb model [4] is described. Testing has been performed on the neural network described precisely in [4]. Experiments to prove OB phenomena [7-8] have been carried out.

The constructed neural network of olfactory bulb bases on experimental data described in [4], in major follows the basic conception. Aforementioned programming environment has been used in olfactory bulb modelling. Parameters of OB model are described in XML language.

Inputs are represented by four vertices, i.e. four types of receptors were examined in model, which react differently on complex odours in adequate odour environment [4]. The results of experiments carried out are followed. Signals of the inputs of groups 1-3 during experiments 2-3 have been passed during conventional time intervals 0–5 and 10–15. In experiments 1-3 the signal has been passed into the last output corresponding to mechanoreceptors during all the time while experimenting. Let’s describe experiment carried out and obtained results in more details.

Testing of Mechanoreceptors. Pure air was passed to input. Consequently one mitral cell only excited. Other principal neurons did not generate action potentials.

Recognition of Odour in Case of Several Types of Receptors are Excited. Stimuli a, b, c, d were passed to inputs in concentration enough for excitation [4]. MC1 and TC14 reached excitation. Cells MC1 and TC14 generated AP. The rest of tufted cells have not been activated except of TC124, which gave a poor response during odour recognition.

Recognition of Full Odorant Spectrum. A full spectrum of stimuli passed to inputs. All receptors were excited. Consequently, all mitral cells and almost all tufted cells were also excited. However with time all of them were inhibited by TC1234.

Excitation of Principal Neurons non-Connected with Mechanoreceptors. In the presence of low air speed complex odorants TC12, TC13, TC123, and TC23 were recognized. There wasn’t air flow component in mentioned odours. It happened only in case when air speed is low – low level of signal at the input of mechanoreceptors in comparison with other types of receptors.

Synaptic Plasticity. We have implemented plasticity of synapses connected with principal neurons. According to computer simulation it is possible to conclude, that aforementioned modification of synapses taken in account in toolbox based on the modelling of plasticity mechanisms results in following. When repeated inputs to receptors passing, the response of corresponding mitral and tufted cells increased in frequency of generated action potentials and in duration of rhythmical activity. It may be concluded, that synaptic plasticity is an important component of short-term memory.

We succeeded to reproduce all phenomena, which had been planned during experimentation. This proves the conformity of toolbox to commonly known morphological, electro-physiological and psychological data.

Conclusions

The system compositional approach to mathematical and computer modelling of certain type of natural hierarchical neural networks is discussed. Fundamental basic components and compositions of the model of elementary sensorium are described. Also basic properties of introduced definitions and notions are established.

Computer toolbox for modelling of informational processes in biological hierarchical neural networks is developed.

A series of computational experiments concerning the functionality of toolbox was carried out on the model of olfactory bulb, where common-known psycho-physical phenomena were reproduced.

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EXPLORATION BY MEANS OF COMPUTER SIMULATION OF NONLINEAR HIERARCHICAL STRUCTURE OF NEURONAL MEMORY ON THE MODEL OF OLFACTORY BULB

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Abstract: Results of numerical experiments are introduced. Experiments were carried out by means of computer simulation on olfactory bulb for the purpose of checking of thinking mechanisms conceptual model, introduced in [2]. Key role of quasisymbol neurons in processes of pattern identification, existence of mental view, functions of cyclic connections between symbol and quasisymbol neurons as short-term memory, important role of synaptic plasticity in learning processes are confirmed numerically. Correctness of fundamental ideas put in base of conceptual model is confirmed on olfactory bulb at quantitative level.

Keywords: thinking phenomena, olfactory bulb, numerical experimentation, model, neural network.

ACM Classification Keywords: J.3 Life and medical sciences - biology and genetics; I.2.6. Artificial intelligence: learning - connectionism and neural nets; D.2.5 Software engineering: testing and debugging; E.2 Data storage representations - linked representations, object representation; H.1 Models and principles; I.5.1 Pattern recognition: models - neural nets; I.6.4 Simulation and modelling: model validation and analysis.