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Hexagonal Approach and Modeling for the Visual Cortex

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Abstract. In this paper, the hexagonal approach was proposed for modeling the functioning of cerebral cortex, especially, the processes of learning and recognition of visual information. This approach is based on the real neurophysiological data of the structure and functions of cerebral cortex. Distinctive characteristic of the proposed neural network is the hexagonal arrangement of excitatory connections between neurons that enable the spreading or cloning of information on the surface of neuronal layer. Cloning of information and modification of the weight of connections between neurons are used as the basic principles for learning and recognition processes. Computer simulation of the hexagonal neural network indicated a suitability and prospectiveness of proposed approach in the creation, together with other modern concepts, of artificial neural network which will realize the most complicated processes that take place in the brain of living beings, such as short-term and long-term memory, episodic and declarative memory, recall, recognition, categorisation, thinking, and others.

Described neural network was realized with computer program written on Delfi 3 language named the first order hexagon brainware (HBW-1).

Key words: visual cortex, thalamus, pyramidal neuron, hexagonal approach.

1. Introduction

Nowadays a great number of neurophysiologists together with theorists – cybernetists have made extended theoretical and physiological studies of the brain activity functions as well as neural networks which an anatomical plausibility are not always confirmed (Rolls and Treves, 1998). In particular, it is not known a non-equilibrium and non-stationary mechanism, information analogous or discrete thoughts process making, semantic of making mind, consciousness, memory and other.

General approaches to the brain functions modeling have been investigating by many researchers for last over fifth decades and today. Beginning from the works of McCulloch and Pitts (1943), Hebb (1949), Rosenblatt (1957), Amari (1983) and continued by Grossberg (1999), Taylor (1999), and many others there were reached advantages in understanding and creating of the brain. It is known that there are the protagonists of the brain analog information processing as well as digital ones. First of them try to treat an existence of only analogous mechanism of information processing in the brain as, they think, a more computationally plausible to the physiological and anatomical realities. As representatives of this view there can be mentioned Edelman (1981), Globus (1992), Reeke (1994), and other. Second of them, i.e., the protagonists of computer metaphor of the brain are much more. Some of them are Hopfield (1982), Amari (1983), Kohonen (1988), Churchland and Seinowsky (1992), Rolls and Treves (1997), Taylor (1999), Garliauskas (1998), Hecht-Nielsen (1998) as well as ones who propagate stochastic and chaotic neurodynamics ideas, i.e., Tsuda (1992), Fuji *et al.* (1996), Watanabe and Aihara (1998), Garliauskas (1998a), and many others.

This paper is intended to present still extra one theoretical view of modeling approach to the visual cortex based upon hexagonal principle using an appropriate network. Our task was not to study all complex processes in detail but rather to catch the typical and most important structural peculiarities in the visual cortex of the brain. The modeling approach to the visual cortex is based on the pyramidal neuron multilevel network with collateral terminates, interneurons and basket inhibitory neurons influence, enhanced mechanism, and hexagonal principle of simulation.

In this paper, the emergency based on surrounds inhibition, the copying competition, enhanced depolarization as well as the first order hexagon brainware (HBW-1) have been considered.

2. Basic Principles of Modeling

Here we would like to discuss some main principles that would be applied for the modeling of the visual cortex functional action. These principles will be based on last achievements of the neurophysiology, an elucidation of the anatomical structure of the cerebral cortex and peculiarities of the information processing.

The first principle is expressed as the equal-distant-connections between neurons one. Pyramidal neurons in the superficial layers of the cortex form clusters of synapses more in remote by some distance (0.5 mm., according to Lund, 1995) ignoring a whole series of intermediate neurons rather than randomly or with nearest neighbours. These regularly spaced excitatory synaptic clusters represent a general feature of neuronal organization for many areas of the neocortex and for many animal species. In such a way, we have possibility to compose a network of regularly spaced neurons with reciprocal excitatory connections in the mass of irregularly arranged neurons. Another aspect of these horizontal connections is that two-thirds of them link neurons with similar properties and one-third connect cells with more or less different properties. Functional meaning of these two different sorts of connections is still unclear. In addition to above mentioned anatomical reason for the regularly spaced neural network, there exist a functional action related to the inhibition process. Among the excitatory pyramidal neurons there are so called basket neurons that exert inhibitory influence on pyramidal neurons within some circular area. According to Lund *et al.* (1995), this inhibition could prevent simultaneously activated pyramidal neurons from establishing synaptic connections within this inhibitory zone, and only connections with neurons outside this zone would be established. If each pyramidal neuron is colocalized with basket neuron, the regularly spaced structure of network would emerge.

The second principle is one of information cloning and spreading on the surface of cortex. This principle enables the invariant analysis of visual objects. The latest is connected with problem of the spatial position of an image within a visual field, rotation and mirror reflection transformations. If we suppose that information about a particular object is represented in the memory locally in cortical area, externally given stimulus will cause the activation spot in the visual cortex, and the activation wave will spread through cortex reaching the memory representation regardless of wherever in the retina the object was projected. Information cloning may be closely related to the formation of associations between different objects represented at some distance in the memory.

The third principle is relied to the competition mechanism in the brain. Neurons, as usually pyramidal ones, compete with each other through inhibitory interneurons excited from the same pyramidal neurons. The inhibitory neurons effect synapses of pyramidal neurons, typically using the GABA inhibitory transmitter. In result the most strongly activated neurons win the competition leaving strongly firing.

Competition may be internal and go on according to excitatory and inhibitory mechanisms within the cortex area, or it may be influenced by external sources, other brain structures, such as reticular formation (associated with general activity or arousal state), associative cortex areas, hipothalamus, and others, associated with attention control, emotions.

The fourth principle concerns the orientation preferences of neurons of the visual cortex. Neurons fires most strongly when a line or an edge of preferred orientation falls within a receptive field of them. Question of the origin of orientation preference remains open for debates. Lund, Wu and Levit (1995) explains this functional property by the specificity of the axon collaterals of some proportion of spiny stellate neurons. These neurons send axon collaterals to either side of the cell body along a common axis. Orientation preference is originated from the anatomical connections of the neurons with orthogonal projections of axon collaterals. All mentioned above principles are not common for all layers of the visual cortex. The first principle is more characteristic for the superficial layers of the primary visual cortex, and the fourth one characterizes basically the middle layers. As the superficial layers could be regarded (with some precautions) as standing higher on the functional hierarchy of information processing, they receive information from the middle layers after preliminary analysis.

In addition, there are two other principles not applied directly in the HBW-1. According to Lund, Wu and Levit (1995) two processing streams in the primate visual process go from the retina of the eye through the layers of the LGN and through the superior colliculi in the area V1. Another hypotesized idea in this work was connected with the pyramidal neurons having intrinsic projections and making long, horizontal, patchy connections within the superficial layers and even with other visual cortex areas spreading over significant larger ones than the local pyramidal neuron dendritic area. Those pyramidal cells paired through axonal terminations (under influence factors of enhancing depolarization) maximum strength their communication and produce entrained firing patterns. Following competition process the winning paired neurons or their clones tend to other horizontal neurons. These neurons having the relation with the thalamus or other cortical regions make long-range connections which are enhanced by reciprocal reverberations with thalamus. There are long-range intra-areal projections on the way of which connections link cells with similar center-to-center distance. It means that it is possible dynamic spatio-temporal copying mechanism including different cortical regions.

Actually, the functional structure of the cortex is much more complicated that it was described by mentioned above principles but this is beyond our hexagonal approach to the functioning of visual cortex.

3. Description of the Neurophysiological Functions of the Visual Cortex

The brain information processing close to thoughts process involves a localized competition process which can occur everywhere in the local region of the brain. Excitatory signals (or abstracted patterns) from the forebrain regions or from the thalamus act through the lateral efferent axon tract (Wilson and Shepherd, 1995) or from the lateral geniculate nucleus (LGN) of the thalamus (e.g., for visual cortex, Lund, Wu and Levit, 1995) to the apical pyramidal dendrites of cortex. The excitatory circuits in the superficial layers provide not only for direct recurrent excitation of the inhibitory interactions but for backward acceptance of information too. These mutual actions are made to different regions of the apical and basal dendritic trees of the pyramidal neurons. Our representation was based on neurophysiological works of Steriade and Llinas (1988), Churchland and Sejnowski (1992), Palaez (1997), Yuste and Tank (1996) and others.

The simplified but close to a realistic diagram of the visual cortex and thalamus interaction is shown in Fig. 1. Here it was regarded the following components: non-specific intra- and paralaminar thalamocortical nuclei neurons, thalamus presented by the reticular, thalamo-cortical neuron clones (layers), Chandelier, stellate and basket inhibitory neurons (in Fig. 1, black arrows mean inhibition, simply ones – excitation), superficial pyramidal neurons (SP_n), inputs (afferences) from the superior colliculi.

Actually neurons in the thalamus make contact with thalamo-cortical, retinal nucleus and local circuit neurons. Local circuit neurons (in Fig. 1 they are not shown) as a transport terminal link the thalamo-cortical neurons with input neurons from afferent information channel depending on states of retinal and two inhibitory neurons in their simultaneity action. Conditional action of these neurons in the terminal provides either for reinforcement or for weakening in the synapses among these different kind of neurons and may even possess, under mathematical point of view, an origin of the conditional probability (Palaez, 1997). An excitation from thalamo-cortical nuclei layer projects to cortical and to reticular neurons. Reticular neurons of the thalamus passes dendrodendritic

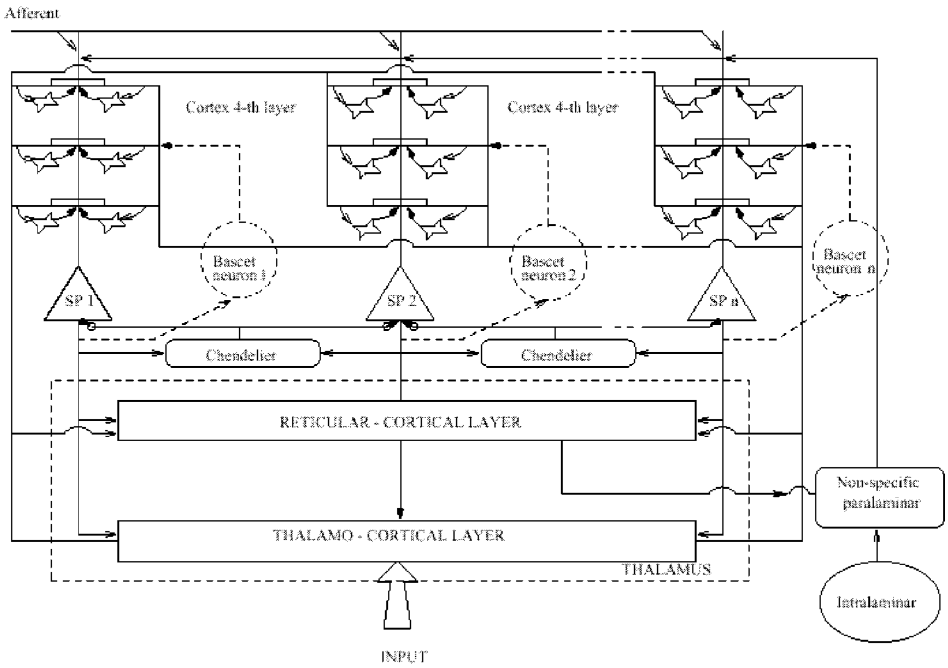

Fig. 1. Functional diagram of visual cortex and thalamus interaction.

synapses and can inhibit each other or thalamo-cortical neurons. The stellate spinous interneurons (they are located at pyramidal neuron spines in 4-th cortical layer and in Fig. 1 are drawn as prolonged stars) inhibit the excitation signal from the thalamus. Their firing frequency is 40 Hz. Chendelier inhibitory neurons inhibit the outputs of pyramidal neurons through the axon hillock as a main point of pyramidal neuron potential generation. Basket neurons regulate by control loop chain the threshold of nearby situated superficial pyramidal neurons. The interlaminar and paralaminar neurons provide control of series impulses by the burst firing with 250 Hz frequency.

This considered functional structure of the visual cortex, area V1, and neurons or their clones in the thalamic nuclei together with adherent terminals, control loops inside and external ones from paraintralaminar nuclei of the midbrain in the first order modeling was simplified to catch main positive peculiarities of the hexagonal principle suggested below.

4. Hexagonal Approach to the Modeling

Specific characteristic of the modeling offered in the present paper is the hexagonal structure of network organization. Neurophysiological-anatomical data confirm the reality of such structure of the cortex. Hexagonal structure is based basically on the principle of equal-distant-connections. As in previously mentioned Lund *et al.* works, interaction between pyramidal and basket neurons could cause regularly spaced network of coactivated neurons which, most probably, should be arranged in hexagons. In such network, each pyramidal neuron potentially is connected with six remote neurons by reciprocal and excitatory connections. Hexagonal structure determines the information cloning. How it is going on?

Hexagons may be regarded as composed of triangles. Suppose, that there are two simultaneously activated adjacent neurons a and b. They will send synchronously impulses to the third neuron (c) and will activate it. Now we have three synchronously activated neurons. But, in its way, b and c are connected with d, and a and c with e neuron, and so on. On the next step, d and e neurons will be activated. Actually neurons generate impulses during the resting state as well, but these impulses are not synchronized and the inhibitory influence maintains this activity relatively weak. It need not be all the impulses from two adjacent neurons to be synchronous to activate the third one. Only some portion of synchronous impulses would be sufficient for activation spreading. According to that mechanism, at least two neurons should be synchronously activated to initiate activation wave that spreads in all directions from initial activation source. In reality, visual information from external stimulus, through the retina and lateral geniculate nucleus, simultaneously activate much more than two neurons-feature-detectors in the primary visual cortex. Formation of hexagonal structure has theoretical basis as well. Theoretical backgrounds in the field of cell sorting based on trivalent maps and its associated triangular graphs were presented by Matela and Fletterick (1979). Based on this work the topological mapping in development biology was considered in the work of Duvdevani-Bar and Segel(1994). The square map approach was proposed by Vasiliev *et al.* (1973) but this approach is more theoretical and far from biological plausibility.

Matela and Fletterick offered a theoretical model for hexagonal structure formation. Their topological approach to the representation of cells suggests that a simulation of a cell system can be based on a planar graph and its geometric map. In the graph, the vertices are the cells and the adjacency of these cells is represented by the edges of the graph. The graph is triangulated: cells always meet at corners with two other cells and form a triangle. Authors derive the triangulation principle from the observations that hexagonal structure is most commonly seen at cell populations. Based on such framework, different authors simulate such processes as cell growth, self-sorting, division, differentiation, adhesion.

As an example, Møller *et al.* (1989) presented neural network model for IVc layer of the primary visual cortex in analyses and reconstruction of distorted images. Depending on two parameters, h_0 and T, presented stimulus induces either stripes or triangular lattice (as correspond to hexagons) phases of the network during stimulus recognition. Hexagonal structure is nearer to the resting state and it may be induced faster. According to Møller (also Hartmann, 1985) the hexagonal theory presumptions may be presented by the main field theory on neural networks. Then Ising spin Hamiltonian can be expressed

$$H = H_{int} + H_{inp} + H_b, \tag{1}$$

where

$$H_{int} = -1/2 \sum_{ij} J_{ij} S_i S_j, \tag{2}$$

$$H_{inp} = -\sum_{i} h_i S_i, \tag{3}$$

where J_{ij} are weights dependent on the distance, S_i, S_j are binary bipolar variables describing the state of neurones ($Si = +1$ is the firing state), h_i is fixed value describing the input from LGN. When $h_i = 0$, the Hamiltonian expresses an inactivated state (all $S_i = -1$).

For the bias term of the system, we have

$$H_b = h_0 \sum_{i} S_i. \tag{4}$$

where h_0 is a positive const for all i neurones.

Main field equation of thermal average (overlap) is as follows:

$$m_i = tanh\Big[\beta\Big(\sum_{j} J_{ij} m_j + h_i - h_0\Big)\Big], \tag{5}$$

where m_i is the average of S_i and β is the inverse absolute temperature ($\beta = 1/kT$). Here T also defines the probability and characterizes as an uncertainty in the firing for the neuron.

The modeling on the lattice with periodic boundary conditions allows to get two types of ordered phases: stripes and hexagons. The control parameters of the phase space are h_0 and T. Hexagonal phase consists of perfect hexagons arranged on a triangular lattice. Hexagonal stimuli for the response of neuronal network is better comparing with random (non-oriented), stripe, square ones. The hexagonal phase is more comprehensive in the parameter space.

5. Hexagonal Network Model

For computer simulation purposes, the simplified hexagonal neural network was created. It consists of three neuron layers (a, b, and c) – three feature maps (Fig. 2). Such network can simulate the processing of images composed on the basis of three features, for example, three differently oriented line segments, three colors, etc. All feature maps are topologically related, i.e., the same location in all layers corresponds to the certain position of an object in the visual field (or object reflection position on the retina). Network elements correspond to the pyramidal neurons of the superficial layers of the cortex. Each layer has parallel input to each neuron which has six connections with neighbour

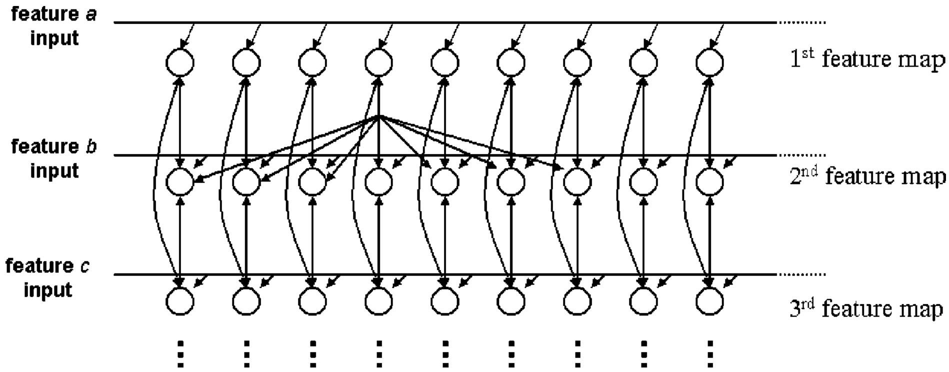

Fig. 2. Scheme of the neuronal connections in the hexagonal model.

neurons of the same layer (horizontal connections) and two reciprocal connections with topologically corresponding neurons in other two layers (vertical connections) (Fig. 2).

Each neuron in each layer is connected with neighbour neurons of the same layer (these connections are shown for only one neuron in the figure) and with one neuron in each other layer.

Actually, there can be as many layers as different features can be detected in a particular area of visual cortex. According to Calvin (1995) cortical structure allows detection of 39 features in any area and that would demand 39 layers for hexagonal neural network. As features there can be line segments of different orientation, different colors, spatial frequencies, movement direction, or more complex structural units. Character of features depends on the certain visual area. For example, primary visual area can distinguish edges or lines of different orientation, higher visual areas (V2, V3, V4, MT) can distinguish more complex features.

Fig. 3 demonstrates the projection of all layers into two-dimensional surface that could be regarded as a superficial layer of visual cortex. Two hexagon matrices corre-

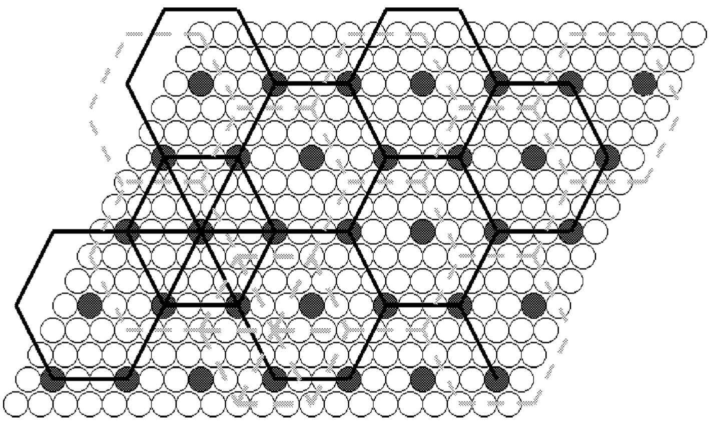

Fig. 3. Structure of the hexagonal feature maps.

sponding to the two feature maps are shown on this example which allow altogether nine feature maps. Input to the network is considered to be information about localization of already extracted features. These could be orientations extracted in the middle layers of the visual cortex, as the output of the neurons of lower hierarchical level. Here presented neural network model does not involve this lower level.

Open circles represent the pyramidal neurons. Two (black and grey) hexagonal matrices represent two feature maps. Nine feature maps are possible in presented example. For simplicity, complete connections are presented only for one hexagonal feature map.

Neural network can function in two stages, learning and recognition (Fig. 4). Simulated network consisting of three feature maps based on the square 100×100 lattice with hexagonal connections are presented in HBW-1 (Appendix A1).

Learning stage involves four processes:

1) Initial activation of three feature maps.

2) Spreading of the activation wave through the future maps (information cloning, as was described earlier). Activation waves from objects confront somewhere on the feature maps and they come to a stop. According to a Crick and Koch (1990), different objects, presented simultaneously in the visual field, induce synchronous but different in phase activation of different populations of neurons in the visual cortex. Phase difference should be relatively small, no more than a few ms.

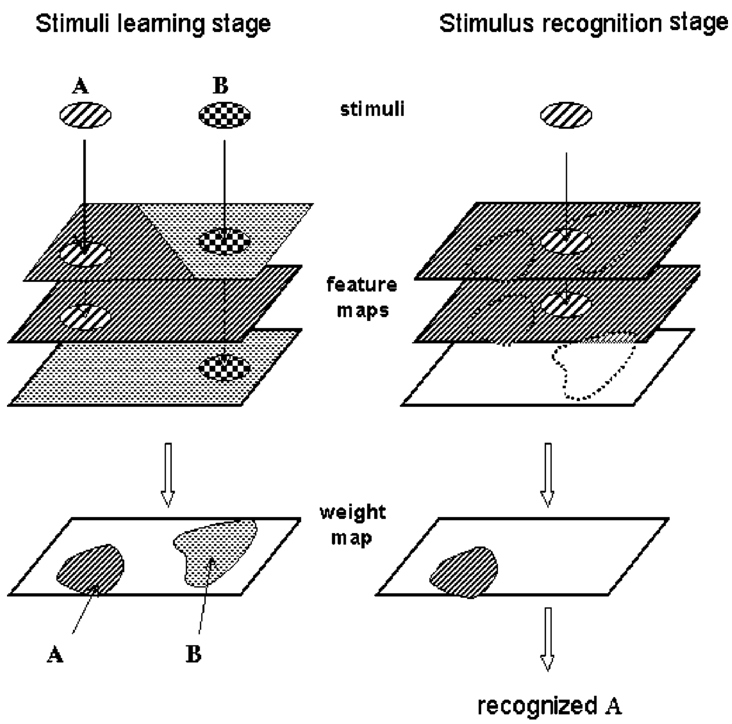

Fig. 4. Stimuli learning and recognition processes in hexagonal model.

3) Localization of activation. Synchronized activation is only temporal and unstable. Due to the inhibition process, this activation is suppressed on the major part of the feature maps after some time interval. Synchronous activation persists only on some areas where it is fed reinforced from other feature maps.

4) Weight map formation. Prolonged activation causes permanent changes of vertical connection strength, as is basis for the long-term memory. Concrete localization of memory representations depends on many factors, such as stimulus character, location of initial activation, previously formed memory representations, and others.

Recognition stage involves the same two processes as the leaning stage, but with some differences. Model permits the recognition of only one object at the same time, therefore, activation waves do not confront with any obstacles and they spread through entire feature maps. The third process, localization of activation, takes place on the weight map in which the localized strengthened connections between feature maps are presented. Activation on the remaining part of weight map is suppressed by inhibition processes. Different known objects induce localized activation in different places on the weight map and it serves as a cue for the final response of the neural network, i.e., the principle of recognition-by-spatial-location is used.

6. Conclusions

1. New hexagonal computational approach was proposed for modeling the functioning of cerebral cortex projected to the process of learning and recognition of visual information in the brain.
2. The main principles of modeling based on last achievements of the neurophysiology, an elucidation of the anatomical structure of the cerebral cortex, and peculiarities of the information processing in the visual cortex were presented.
3. Based on theoretical background of a hexagonal topology and concrete hexagon's arrangement of excitatory connections between neurons, the basic principles (equal-distant-connections, information cloning and spreading) of hexagonal neural network were newly formulated.
4. The first order hexagon brainware (HBW-1) was constructed and applied for experimental dynamic modeling of the visual processes in the brain.

Appendix A1. Hexagon Brainware (HBW-1)

Described neural network was realized as a hexagon brainware (HBW-1) – computer program written in Delfi 3 language in Windows 95 environment. Basic program algorithms are presented in Fig. 5. Input to the HBW-1 are the number of objects (n) to be learned and their feature codes $(f(i))$. Object feature code is a binary sequence of three digits, e.g., 011. For the algorithms of "Creation of activation" and "Spreading of activation",

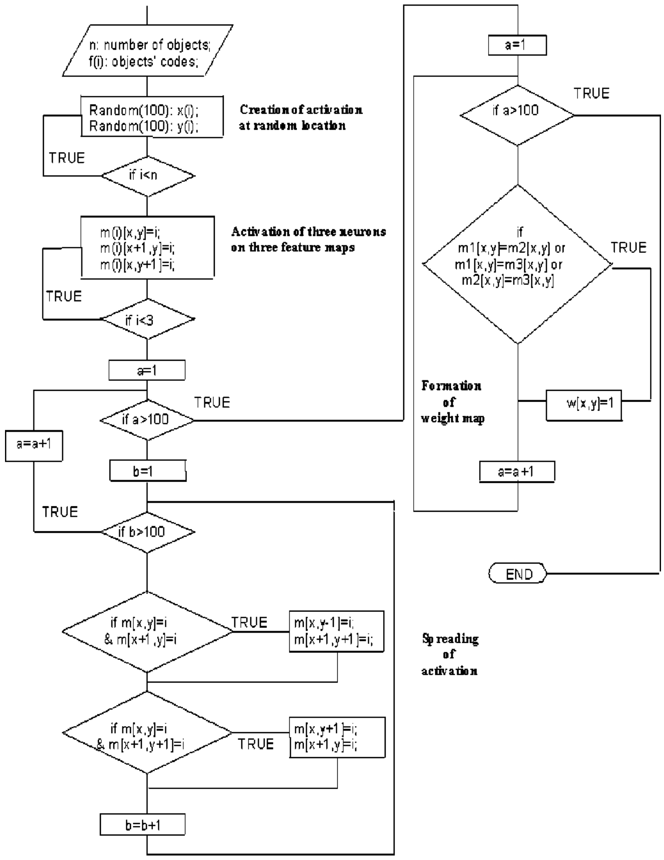

Fig. 5. Block-diagram of the basic algorithms in the stimuli learning stage.

variable i represent the number of object, and it is equal to 1, 2, or 3 in the case when three objects are processed.

HBW-1 consists of three feature maps and one weight map that are based on the 100×100 square lattice. Simple algorithm was applied to square lattice to convert it to the layer with hexagonal connections. All stimuli were presented to HBW-1 simultaneously and at random locations at the beginning of learning stage. Stimuli were simple objects consisting of two or three features. Each stimulus feature simultaneously activated three neurons in the corresponding feature map. Spreading of activation was based on a two-one rule-two active neighbour neurons activate one passive neuron in either direction (there should be noted that network structure with hexagonal connections predetermines that two neighbour neurons have connections with two other neurons except two neurons on the border of two-dimensional layer). Further learning process was going on according to earlier described scenario. At the end of learning stage, active regions on the weight map were assigned to corresponding stimuli and their particular features, and the locations of these regions were memorized by HBW-1. During recognition stage, stimuli were presented by one at a time at random location and further recognition processes were performed as described earlier. Recognition of stimuli was successfully executed by HBW-1.

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Heksagoniškumo principo taikymas regos žievės modeliavimui

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Siūlomas neuroninio tinklo koncepcinis modelis, realizuojantis smegenų žievės anatominius ir funkcinius ypatumus, sąlygojančius heksagoninę funkcinę neuronų struktūrą. Neuroninis tinklas HBW-1 realizuotas kompiuterinėje programoje, vykdančioje vizualinės informacijos įsiminimą ir atpažinimą.