THE MODEL OF HUMAN VISUAL LONG-TERM MEMORY WITH ABILITY FOR GENERALIZATION.

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Summary

A model of human visual long-term memory with ability for generalization has been synthesized. Perceptive structure of the system may be either parallel (multilayered retina) or successive (a network scanning a contour by tracing).

The synthesized model of retina performs a number of transformation of information as in a visual analyzer - such as intensification of contrast between an object and its background, contour or outline extraction, reaction to the movement of an object (in a particular direction at a certain velocity).

It is the code tree that is used as a structure for storing codee in long-term memory. This structure explains the dependence of the response time upon the number of alternatives and allows studying the dynamics of the following trajectoria (path) reduction occuring during learning process.

A model of human long-time memory presented as a structure of a tree consisting of neuron models is described and such processes of information transformation in it as recording, storage, generalization, reading, disposition set to the given type of signals are considered. The perceptive structure of this system may be either successive (scanning) or parallel (multilayered retina).

There are various kinds of scanning: a) successive, ranked, one-channel tracing of the contour and the formation of primary codes-b) distant,uneven tracing on characteristic points of ob - jects and the formation of secondary codes. c) transition to the parallel multichannel scanning through the retina.

During the tracing the contour is divided into segments according to a definite rule. The number of segments is determined by the contour configuration only. Each segment is characterised by a ranked group of the primary signs $(\alpha, \beta, \gamma, \delta, \lambda, \varepsilon, h)$ which are functions of its curvature. The primary code is a table in which the number of lines and columns corresponds to the number of signs used and the number of segments of the contour.

The use of the one-channel contact tracing brings us to the necessity of introducing information about the entire perimeter in the form of a definite simple sequence, which reduces the rate and increases the number of limitations on the condition of perception. Digression from the contact method of perception made it possible to elaborate the corresponding extended secondary signs of the object and to form the secondary code, out of them. The secondary codes are more generalized and shorter than the primary ones (they are one line instead of a table as is the case with the primary codes) and they simply correspond to an object, the sequence of presenting the signs being of no importance. The use of the secondary codes in the process of identification made it possible to trace characteristic points of an object irrespective of the sequence of the tracing, which reduces the number of limitations on the object under perception and makes it possible to place it into the field of vision irrespective of sequence. Besides this the characteristic parts of an object may be presented, not an entire object.

The secondary codes are invariant with respect to orthogonal, similarity, affine transformations of the contour and transformations of the central projection within definite bounds as well.

The code tree is used as the long-time memory structure for the primary and the secondary codes. This structure explains to us how the time of the reaction depends on the number of alternatives, makes it possible to fix how often separate events occur, and to examine the dynamics of the tracing trajectory reducing while training (learning).

Multichannel parallel introduction of information about visual objects into memory is performed through retina in the model. This means that a certain retina structure will provide for the investigation of an object in a definite sequence, division of the information thus obtained into pieces and its investigation by these pieces.

Assuming that sensitivity of perceiving elements of the visual system changes so that at every moment sensitivity of only one group of elements exceeds the threshold while that in other groups does not reach it (the threshold) only those parts of an object are picked out simultaneously that are projected on the elements of high sensitivity. Hence, an object is picked out successively by certain parts, and every part is picked out parallel to working elements. In this case we have the system working parallel-successively.

In case we have parallel, not successive introduction of information on a uniform retina it may be demonstrated that while the thresholds of the elements of retina change according to a periodic law, the information about the object is transferred from the retina to memory successively by parts, the nature of succession being dependent on the object properties. However dependence is different from that when the contour is traced. It means that the stabilized (motionless with respect to the retina) object can be perceived and introduced in memory.in these conditions) too.

Transition to such a type of perception is also a kind of tracing the closed cycle which is set by a period of threshold changes, the dynamic process of threshold changes being independent on the movements and may be set centrally, which quickens the process of perception. Periodic changes of the threshold make it possible to obtain a series of codes of one and the same object (ranked according to the law of element sensitivity changes). Formation of the group of codes of one object, the group connected with the inner period of the perceiving elements sensitivity changes without the outer transformation of the object enables one to make an approach to the explanation of certain aspects of the constancy of perception mechanism.

Thus, when the visual system works in a successive-parallel way the movement of the tracing system of the eye may be replaced by the dynamic regime of the perceiving neurons' sensitivity changes.

She model of the retina is a structure consisting of homogeneous elements. Each element is a multi-layered network. The first layer is the receptive field of an element. The second one consists of novelty neurons. This layer picks out brightness changes in the receptive field and, thereby, the object's border. The third layer consists of summating neurons. The line curvature is detected irrespective of the line orientation in this layer, i.e., the element in this layer yields the output proportionate to the line curvature in the receptive field. The fourth layer consists of difference neurons and responds to the movement of the picture and performs selection of the time-space code, picking out certain gradations of the curvature (Pig.1,2).

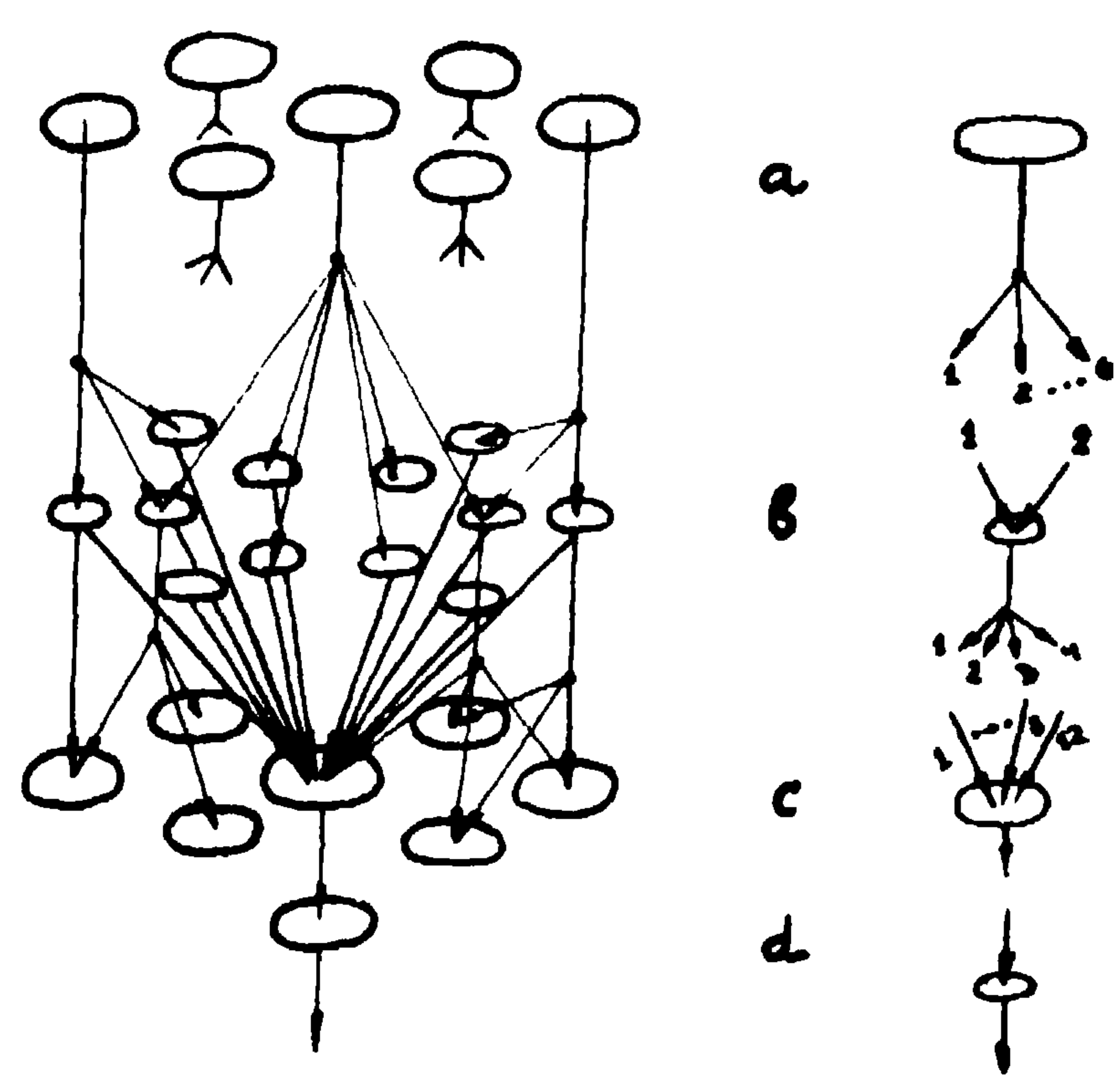
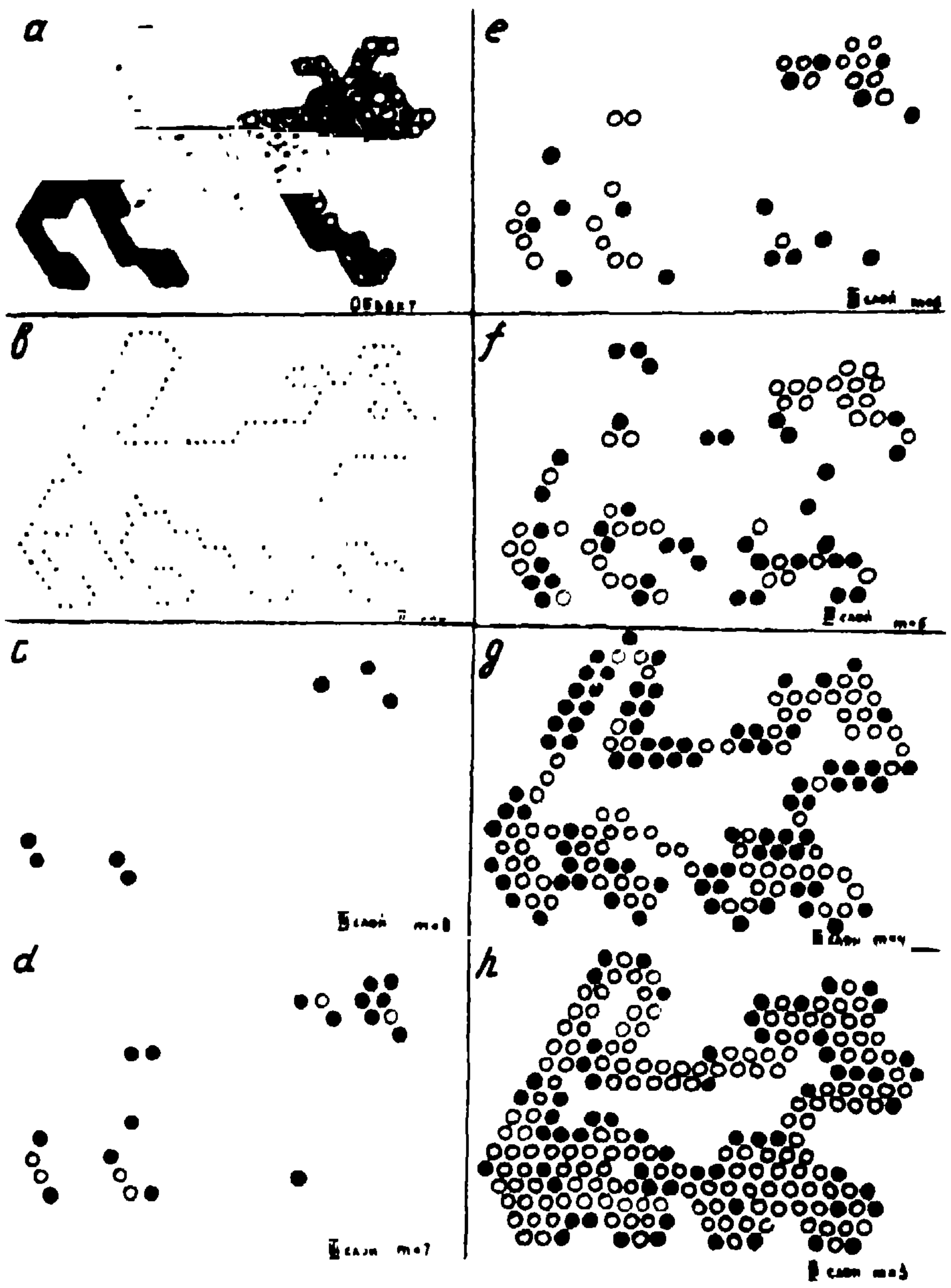


Fig.1 Model of retina main element. (a) The first layer - the receptive fi-

eld of an element, (b) The second layer-novelty neurons, (c) The third layer - suimnating neurons, (d) The fourth layer-a difference neuron. The types (b)-(d) neurons equations are shown in the figure 6 of the report "The model of Human Short-Term Memory" by I. Ja.Beresnaya and R,M.Granovskaya,



Fig,2 Object perception by the model of retina.

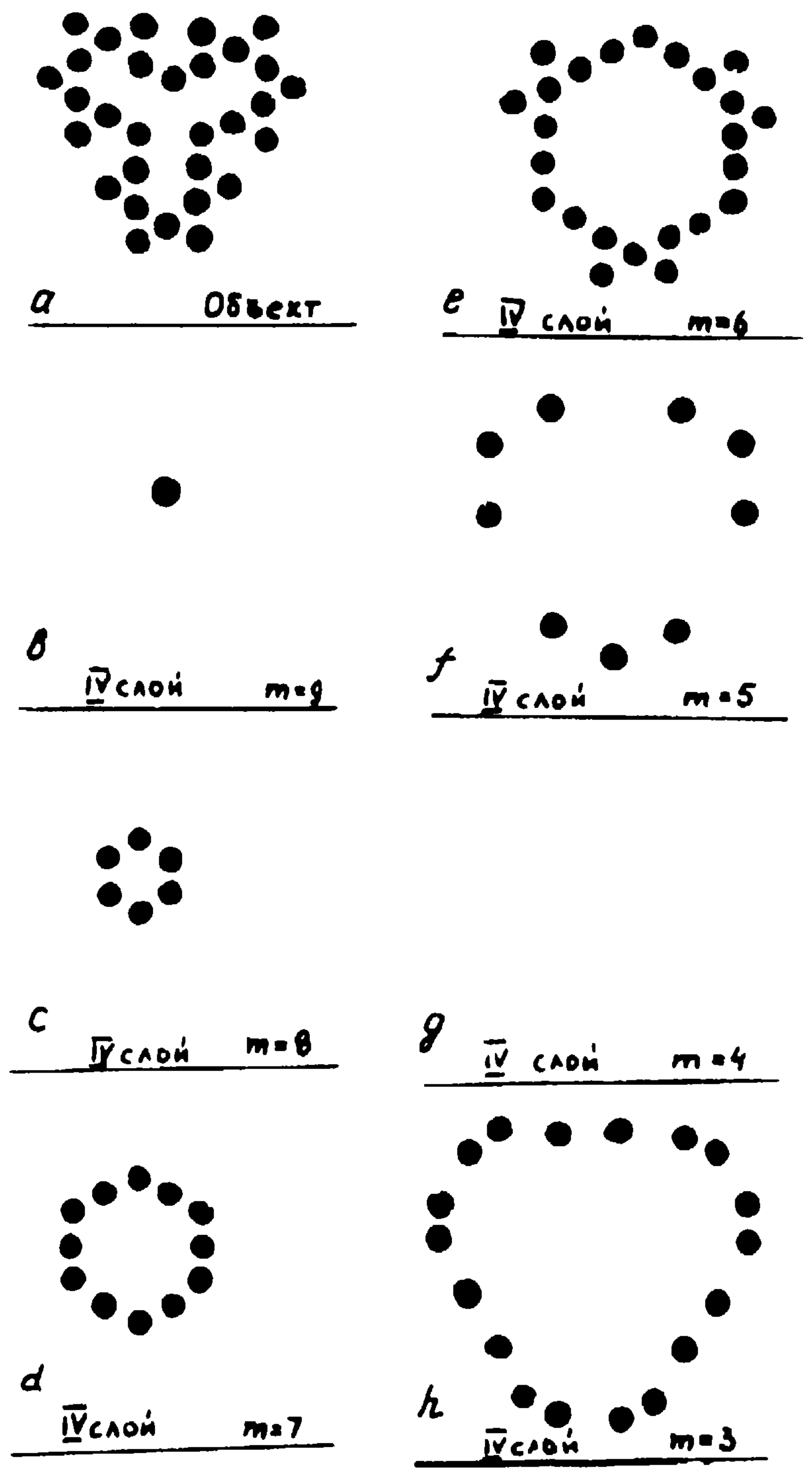
(a) The first layer - an object, (b) The second layer, (c)-(h) The third layer at successive time moments t_3-t_8, when neurons threshold value changes from m»8 to m=3

Thus codes of object pictures at retina output are invariant with respect to all the orthogonal transformations, namely, a turn, parallel transition of a picture and mirror reflection.

The fact that there is no division of the neuron receptive field into exciting and inhibiting zones is the specific feature of the given retina model.

The offered retina model makes it possible to illustrate the psychological phenomenon of illusionary movement which consists in the perception of the seeming movement of one object, although two objects are presented successively at different points. The reaction to the signal change either in space or in time is the main principle of how all the layers of retina operate. The operation of the given retina is considered as a model of separate stages of visual objects perception (Fig,3).

The memory model is either three-or two-dimensional code-trees, one- or multi-layered, dichotomous or K-tomous, built of homogeneous or heterogeneous joints and elements- what is common about them is a structure resembling a tree. The usage of the code tree as the main structure of a long-time memory has great advantages over other types of memory arrangement, as for example the teaching matrix. Such structure makes it possible to use fewer elements than when codes are stored as an infinite sequence, which increases the rate of arriving at a decision when the code is searched in memory.



Pig.3 The illustration of the psychological phenomenon of the illusionary object movement.
(a) The retina first layer - an object.
(b)-(h) The retina fourth layer at successive time moments when a neuron threshold value descends from m=9 to m=3.

The process of recording in the offered memory model presented as code trees is arranged so that a successively ranked set of object signs arrives at the input either directly from the outer input or from the output of the short-time memory. Bach of the element after missing a certain code is inhibited while the code continues to be recorded in the upper layers of the tree. This results in the successive recording and reading of the codes.

In a situation like this a spatial code tree that makes it possible to reduce the number of alternatives in the tree joints is used for the storage of primary codes.

A two-dimensional code tree is also used as a structure for the storage of secondary codes. Each gradation in such a tree will have its corresponding branch, each code - its separate way, each sign - its layer. The identical codes will have their identical way, the repeating codes do not alter the tree configuration.

Accordingly$_9$ the tree will have as many layers as the number of signs used and as many ways as the number of different codes arriving at the input of the memory system. Bach way of the tree is ascribed its weight proportionate to the number of the corresponding codes that arrived at the input of the memory system.

The only way corresponds to the full code arriving at the tree input, The end of the way is connected with the corresponding index. Besides this index, indexes of all the joints lying in the given way can be counted. In case we have several ranks of the code arriving at the input, note the full code reading may be performed with but a certain degree of relativity (Fig.4,5)

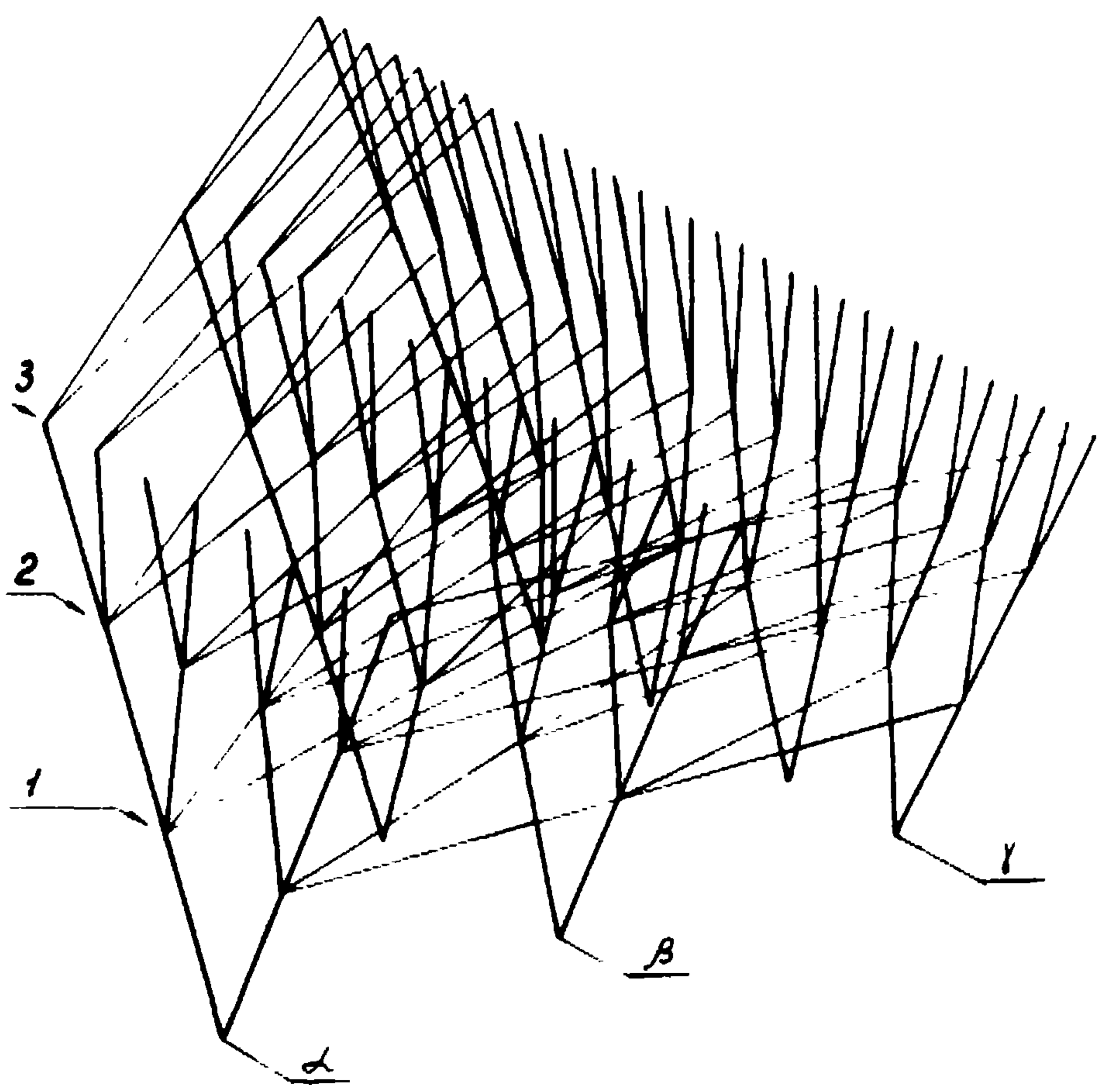
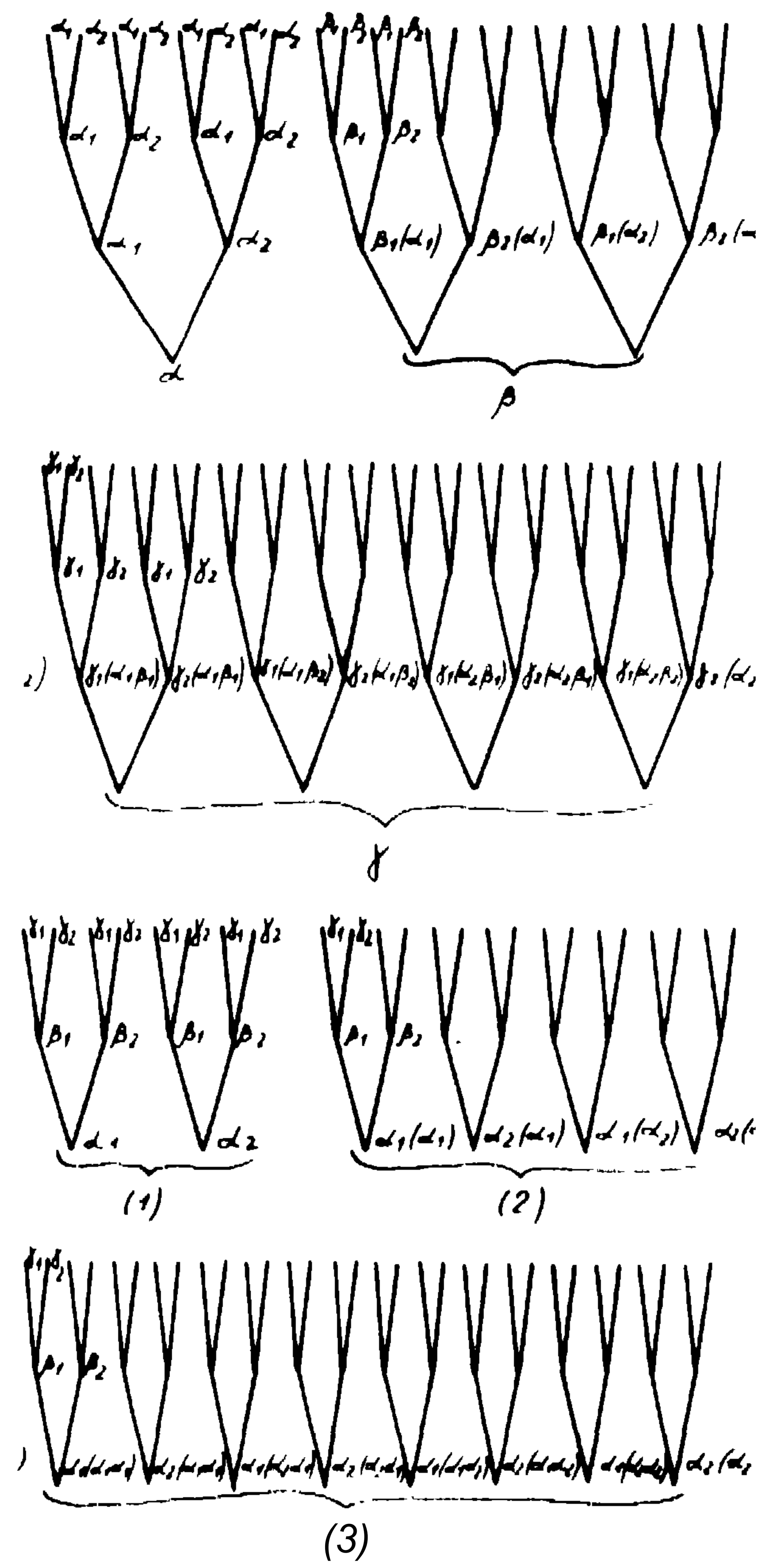


Fig.4 A space code tree formed when successive one-channel tracing of the contour (primary signs α, β, γ): α, β, γ - vertical plane code trees, 1, 2, 3-horizontal plane code trees.

The tree structure provides for the only descent (simple identification) from any joint down to the tree foot while the reading takes place. If signs are different as to the number of gradations, the number of elements of the tree will depend on the succession in which signs are to be applied. The number of elements will be the smallest if the signs are applied so that the number of gradations increases. Omission of non-ramifying ends of ways in the full tree can serve as the following step to economise elements.



Pig.5 Aplane code trees (α, β, γ, 1, 2, J) that form the fig.4 space code

tree.

When the arrival of signs in the code is ranked, the memory structure is economized. First, the arrival of the code of the same object with a larger number of signs does not require additional code recording: second, the ranking of signs according to the number of gradations or to their importance makes it possible to reduce the number of steps along the tree so that the identification is with the same degree of accuracy, i.e. the ranking is advantageous as to the process rate.

When the ranked system of signs is used, the tree structure enables one to increase their number while the codes already in storage are not changed. This enables one to analyse objects and record codes with any degree of accuracy needed, moving from the tree foot up to its summits as it is relevant in some cases to adopt decisions at the expense of a rough classification and at the same time to reduce the time of decision without going up the tree. Such structure makes it possible to perform a simple recording and code reading by its index which is compared with one of its summits. Recording and reading are performed without address in this structure, associatively (in so far as the code has no special address group) and the code arrangement on the tree is determined by the code properties only, the structure of its signs.

While reading, a complete shuffling of the codes in storage is not performed the needed code or a group of nearby codes are read immediately, which quickens the process of reading. The time of selection does not depend on the bulk of the information recorded, being determined by the number of layers in the tree only.

The measure of depth of the code in storage has been introduced. It is presented as weights of those branches and joints of the tree which store information of the given code. The weight is connected with the changes of synaptic coefficients of those elements which the codes traverse in the process of teaching.

Weights accumulation in the tree structure is compared with the frequency of occurrence of the given code at the system input. If sequences with the maximum weight are read out off memory they will be the codes that have been most often presented in the history of the system.

It has been shown in the model that the optimum uneven strategy of the potential hypothesis check-up can be elaborated on the basis of the statistics in the tree accumulated in the process of teaching and the trajectory of the object investigation changes as the result of this. Thus, the brain produces a sort of reflection of an object which is expected to be on the retina; and this brings about changes in perception and speeds up the process of identification.

Arrival of information about new objects brings about changes in weight and in pseudoweight as well, i.e., there is accumulation of information in the memory structure not only about the codes that arrived earlier (weight) but also about these ones that are similar to them according to a certain criterion of 8imilarity, i.e., codes are generalized by their similarity, the similarity being determined by the nearness of the signs arrangement in the memory structure or well by the nearness of signs in the ranked sequence when they arrive at the memory input (pseudoweight).

The usage of pseudoweight makes it possible to reduce the period of teaching (learning) through the reduction of the teaching sequence and to teach the system of memory with the help of the most characteristic representatives of the class, only bearing in mind that a sort of intermediate relief stretches automatically between the excited parts of memory. Such a system starts responding to objects that were not presented earlier but are part of a class of such objects and are similar to them according to certain criteria. The system responds to the objects as if they were known to it.

The usage of pseudoweights makes it possible to optimize (reduce) the teaching sequence according to the criterion needed and thereby reduce the process of dictionary of objects.

The introduction of weights and pseudoweights makes it possible to approach the modelling of such important psychological process as the formation of a unit determined by the immediate prehistory.

The usage of pseudoweights also makes it possible to extrapolate properties of nearby objects i.e. to solve the task before its exposition is over or even by way of an imaginary experiment with it.

Assuming that there is a certain tree structure, homogeneous as concerns its properties before the teaching, the structure will grow more and more heterogeneous in the course of teaching in so far as the changes in the distribution of weights of branches and joints go. The greater the number of different codes that arrived at the given memory structure, the greater the number of tree joints used, i.e., the history of the system gradually goes up the initially homogeneous tree, i.e., it sort of grow grows. The heterogeneity thus appearing is isomorphous to the group of the passed codes both by the nature and the area it spreads over and makes it possible to restore the history of the system with a certain degree of accuracy later on.

After the memory structure had passed through a certain sequence of codes it is a heterogeneous system consisting of ensembles of functional elements with the rate of processes varying in different parte of the system and the signals pass from one joint to another with the varying probability. Values of the processes rate in the ensembles and the distribution of weights of the branches that determine the branch the process will spread through are determined by the prehistory of the system in the process of teaching only. The usage of a special system independent of the input sequences to control the thresholds of the functional elements of the tree in the model makes it possible to approach the explanation of how the importance of the task and its emotional colouring influence the narrowing of the solution search zone.

When such system is launched the way the given code in the tree will follow will be determined not only by the prehistory of the memory system but also by the changed sensitivity of the upper joints of the tree. In this case the code will follow another branch and will bring about another solution (it is identified with another index).

The measure of novelty of the solutions thus obtained is determined by the number of potential prolongations from the given joint. If there is a group of ramifications the weights of the sum of prolongations being equal, the changes in the sensitivity of one of the upper layers will essentially narrow the search zone, i.e., the task in this particular case comes out as a factor of the search directness and determines the formation of the unit connected with the signal importance.

Reduction of the identification of printed letters of the Russian alphabet has been considered as an example of reduction of the process of identification Primary codes concerning signs α, β, γ, δ, λ are patterns of letters by the successive scanning. It has been shown that the greater the number of signs used the smaller the number of groups of the primary code and the corresponding part of the contour required for the simple identification. When only one sign α is used the alphabet falls into 18 groups, when signs α and β are used there are as many as 28 groups. All the letters are mutually separate with a larger number of signs. The average number of intervals per letter necessary for the identification will be 13,3 in case all the five signs are used the number of intervals will be 4 (Pig,6).

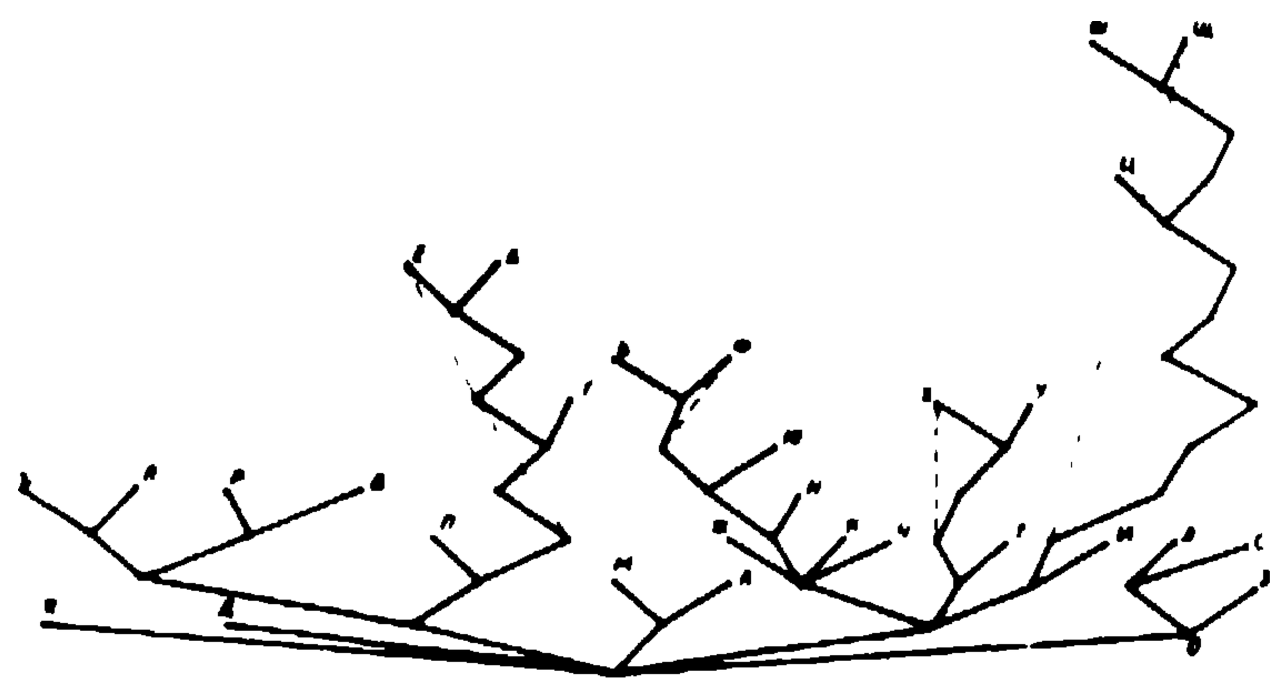


Fig.6 Russian letters code tree when letters contours are traced successively

Further reduction of the process can be achieved at the expense of transition from the continuous tracing along the contour line to the uneven one.

tion and value of the leap are determined by the hypothesis put forward on the basis of the analysis of the upper part of the tree structure. The leap must result in the hypothesis check-up (Fig.7).

When information about letters of the Russian alphabet is introduced in memory with the help of retina all the letters are subdivided into groups whose number depends on the number of gradations of the retina elements sensitivity. It has been shown that if the number of gradation tions is six. All the letters are discerned by the retina. The smaller the number of gradations the rougher the classification i.e., several letters find themselves in one and the same group(Fig.8).

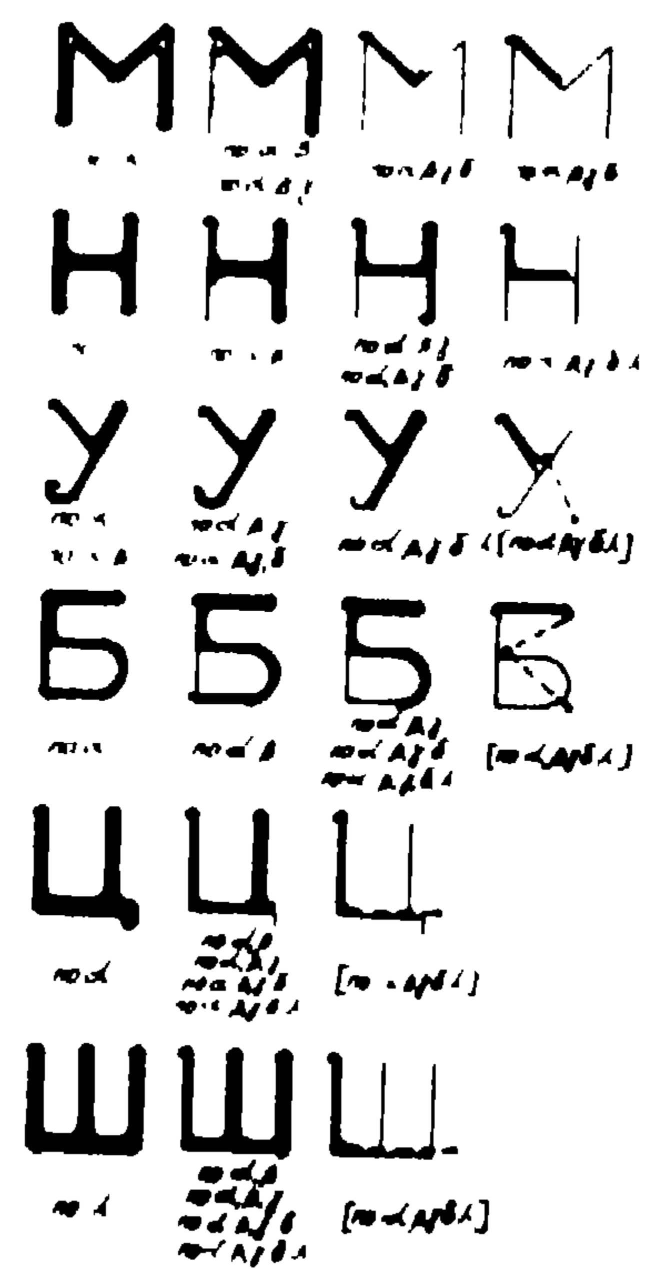


Fig.7 The reduction of Russian letters contour tracing during identification concerning signs α, β, γ, δ, λ.

The organization of memory according to the principle of the code tree makes it possible to perform the object identification through successive approaches while going from the foot of the tree to one of its summits. The change of hypothesis from a more general to more particular one up to the precise identification takes place in the process of such a movement.

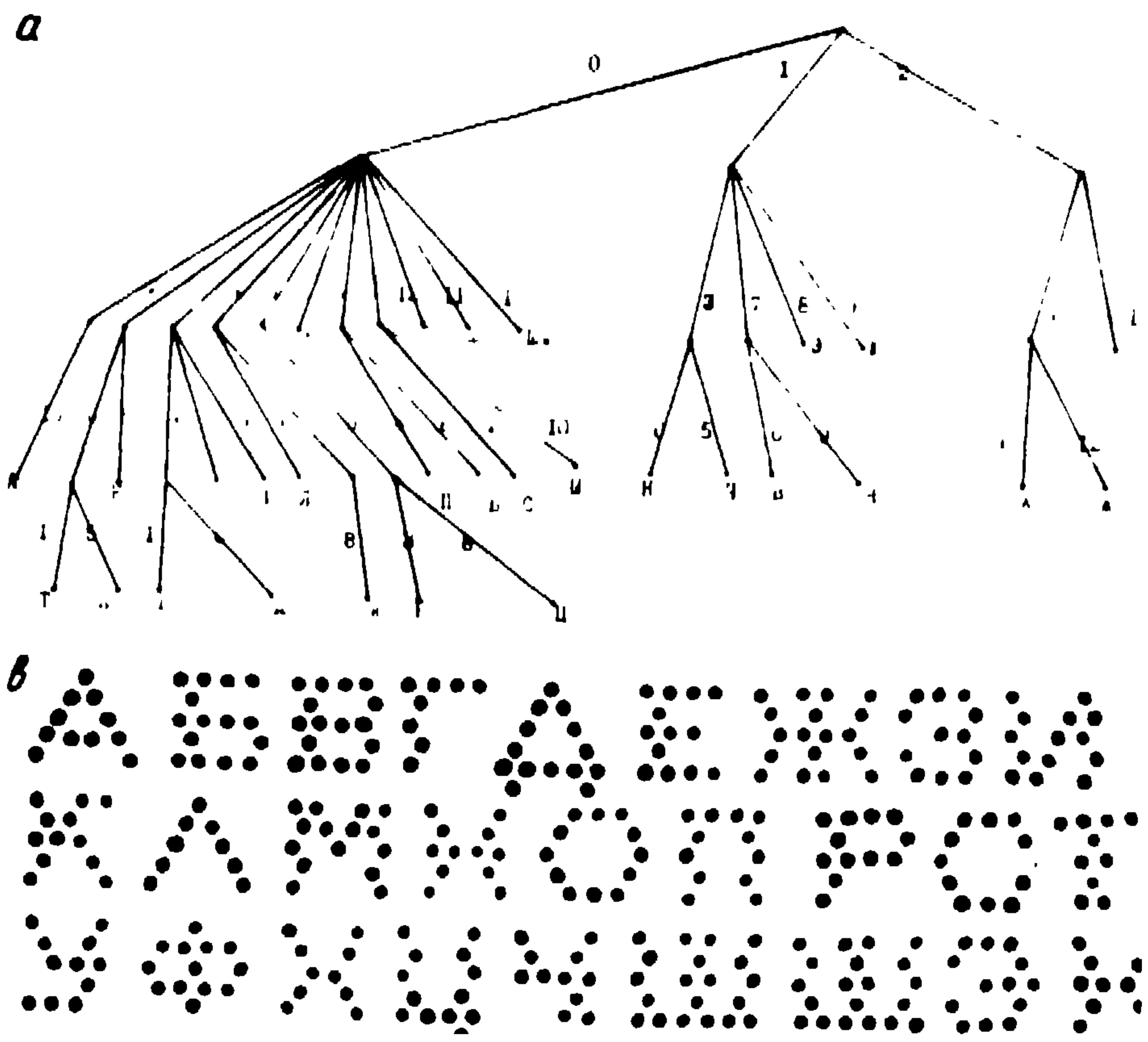


Fig.8 (a) Russian letters code tree after parallel multichannel scanning through the retina model when the model fourth layer neuron has 6 sensitivity change ranks, (b) Russian letters on the retina model.

THE MODEL OF HUMAN SHORT-TERM MEMORY

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Summary

The short-term memory under consideration differs from other memory systems of the same sort in so far as it has the following properties: (a) storage of codes in the dynamic memory and analysis of codes are combined in time; (b) information is stored in both structures (dynamic and static) in a "squeezed" form and the degree of "squeezing" differs for dynamic and static memories: (c) codes may be restored both out of dynamic and of static storage.

The model of memory proposed is invariant relative to the object's size and to changes of the object's position on the plane, to its negative image and to the object plane turning about.

The basic requirements put to memorizing devices of computers are those which provide for an increase in their capacity and the rapidity of their action.

The increase in the capacity of the memorizing device leads now to a reduction in the rapidity of its action as the time needed to find objects of information at large increases and so does the addressing part of the code - descriptor. Hence, requirements put to memorizing devices while elaborating new computing systems, i.e., greater capacity and greater rapidity of action are essentially mutually contradictory. Human memory by far excels the best artificial storing devices in so far as flexibility, capacity, the rapidity of the selection of information are concerned.

This contradiction makes it necessary to syntheeise new memorizing devices on bionic principles, i.e. on the basis of human memory and studies of higher animals, and to transfer corresponding principles and regularities to information storage techniques. Unlike memory blocks in computers which provide for a clear understanding of the mechanisms and principles of information storage, mechanisms and principles of how memory works with man and animals have been but vaguely studied so far and the way they process information may be surmised only through a series of indirect indices and almost exclusively by way of comparison of the time-space distribution of signals bearing information at inputs and outputs of the system.

These processes differ one from the other in so far as the manner for the storage of information (neurodynamic process and stable structural changes), the time of its storage (hours and life time) and the type of the agent destroying traces are concerned. This investigation pursues the following tasks, (a) The formalisation of the main physiological and psychological data proceeding from mechanisms of functioning and properties of structural elements of the operative (short-term) human memory, (b) The construction (synthesis) of a mathematical model of the short-term memory out of neuron-like logical elements, a model which would not contradict psychological and physiological data, (c) An analysis of the work of the model in systems for recording, storage and reproduction of information, (d) A comparison of properties of the model offered with the memory of living systems by some parameters.

Certain principles of processing information in human short-term memory are used in the model: the transfer of the information arriving at the input successively to spatial distribution of traces, the combination of the process of analysis and that of storage, the storage of information in a squeezed form, which enables one to generalize it

In the model under investigation the the information arriving at the input of short-time memory (SM) is stored successively in two different forms: first, as a dynamic process on a certain neuron structure, then as a static distribution of spatial properties of the neuron structure. The size of information in the dynamic form of storage is limited. The size of SM as to the number of structural elements is also limited.

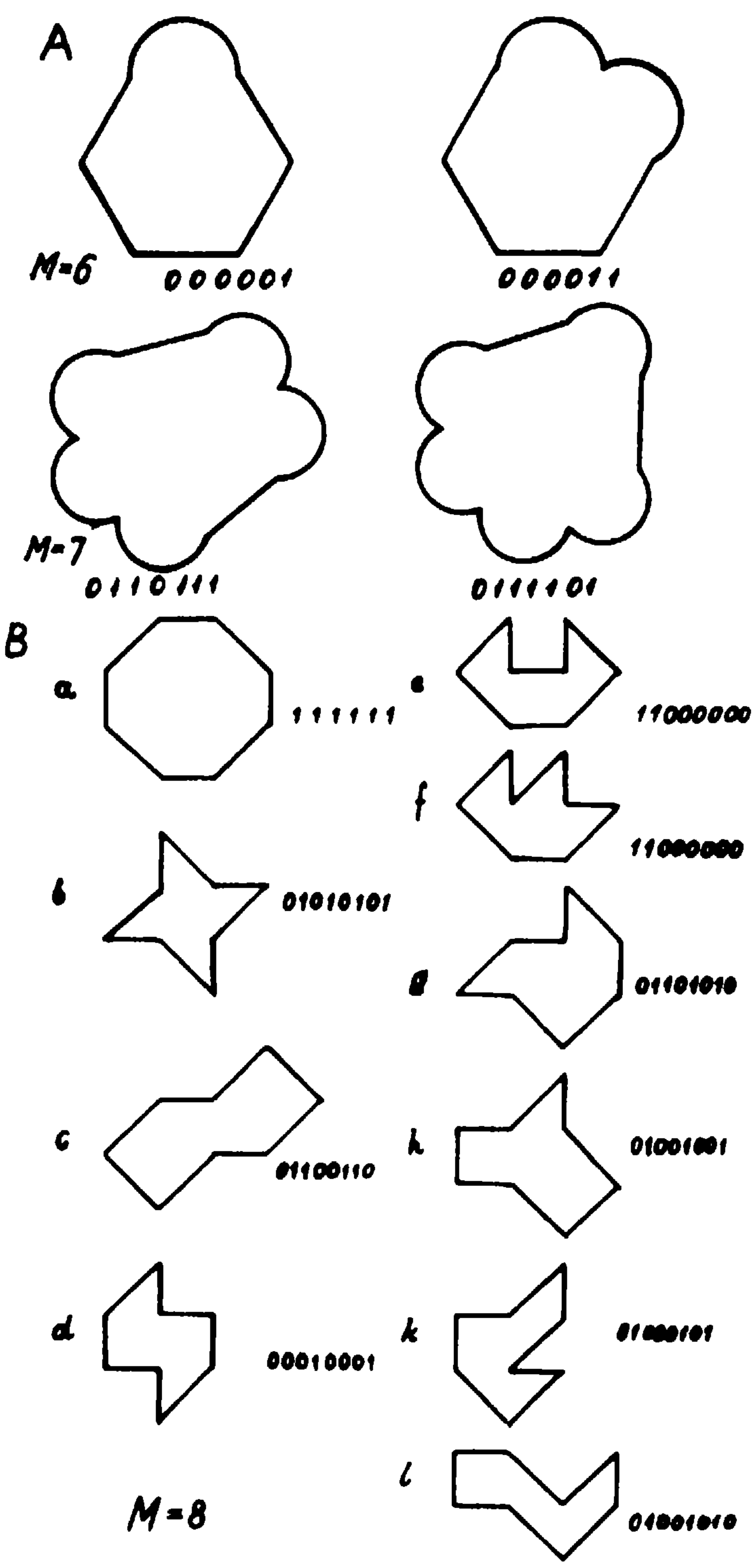
The period of fixation of information over other information may be introduced in SM, the information in the dynamic form of storage being erased. Information arrives at the input of the SM model from outputs of receptive and processing neurons (which pick out signs of the object and form the primary and secondary codes) successively in time.

Simple arbitrary geometrical figures were chosen as objects bearing information which enters SM model. Each figure is a closed broken line - contour of a polygon. The broken line consists of segments with the length of 1 and (the side and the diagonal of a square). Contiguous segments of the broken line form angles of 45°, 90° and 135°. All the figures are subdivided into ranks according to the number of their apexes.

The rule of polygon angle evaluation may be also formulated as follows: in case of clockwise trajectory of eye - tracking system while tracking the polygon angle, the interior angle of the polygon must be evaluated: in case of counter-clockwise trajectory, the exterior angle of the polygon must be evaluated. The interval is coded as one, if it includes the angle of 135° and as zero if the value of the angle is 45° or 90°. While coding, the figure contour tracking is performed clockwise and may begin at any arbitrary point. One may assume that in some sense the codes of the figures under consideration characterize the succession of concavities and convexities of their contours.

One more class of figures is used as the input objects. These figures are constructed like this. Some sides in a "right" polygon are changed to half-circles (circumferences). These half-circles are constructed on respective sides of the polygon, the latter being their diameters. The figures obtained contain both straight and curved sides. All the figures are subdivided into ranks according to the number of their sides. Fig. 1,A shows one figures of ranks V,V1 and their codes. The curved side is coded as one, the straight one is coded as zero. The only binary succession corresponds to every figure of this class.

The simplest linear uniform circuit without ramifications consisting of models of neurons is used in the model under investigation as a structure to store information in the dynamic form. This structure is called the main chain (MC).



Pig.1,A. Different rank (M=5,6,7,8) figures and corresponding codes. B, Rank M=8 figures of another class and corresponding codes.

MC is composed of successively connected on-off neurons with one input (n=1) without memory (s=1) and threshold m=1 (Pig.2). The equation of the element m is as follows:

p(t+1) = fifleCt+l) - e(t)| - m(t)] ,

$$E(x) = \begin{cases} 1, & x \geqslant 0, \quad p(t) - \text{output signal}, \\ 0, & x < 0, \quad e(t) - \text{input signal}. \end{cases}$$

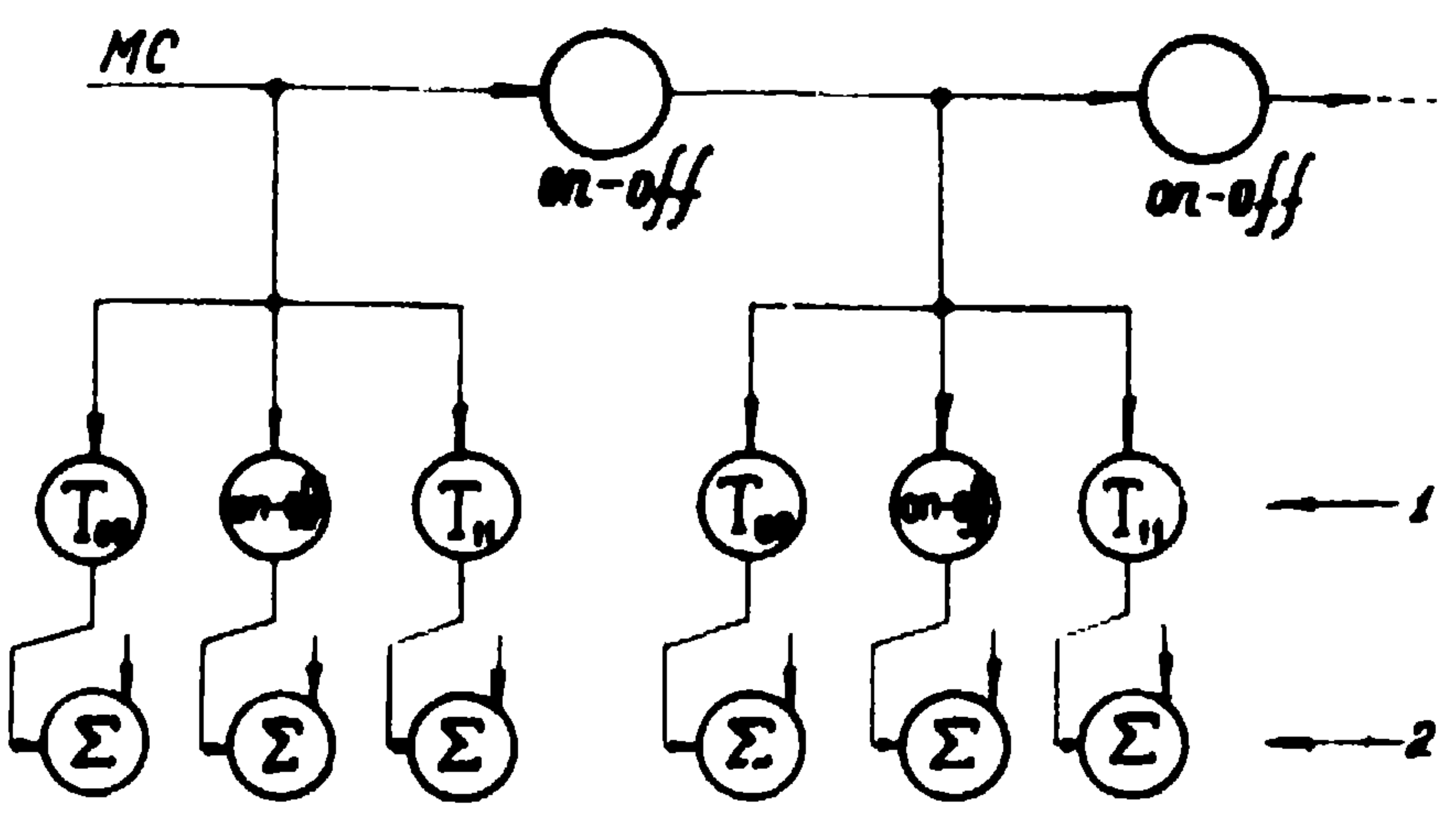


Fig.2 Main chain. Organization of static storing network (there is no restoring network at the figure)· 1 - indicators, 2 - counters.

The storage of the input code in the dynamic form is compared with the state of the elements composing MC at the given moment of time which is conditioned by the type of the input code and its transformation on every neuron of MC.

A separate symbol of the output code of every neuron is determined at a certain moment as modulo 2 sum of the input symbol for this neuron at the tact (moment) under consideration and the one proceeding to it. The value of the output symbol of any neuron in the MC depends on the structure of the chain Neuron number) and on the symbols of the input sequence.

In spite of the fact that all the neurons composing the MC are identical each of them "picks out" a definite sign of an object, the nature of the sign being de by the neuron number, i.e., with the arrangement of the MC like this the division of the functions of the analysis of the object's code along the chain takes place.

The output sequence of a MC neuron is determined at the given moment by states of certain neurons, not by those of all of them. It has been shown that the total amount of neurons whose state determines the output sequence of every neuron is always even, and the numbers of these neurons are symmetrical with respect to the middle of the chain.Whatever the number of neurons in the MC, the value of the output symbol of the n neuron necessarily depends at any moment on the state of the first neuron n tacts back from the moment under consideration and on that of the n neuron at the given moment. It has been revealed that the value of the output symbol of any neuron of the MC is connected with the number of units in the row of the so called residue modulo 2 triangle where the row number n is equal to that of the given neuron (Pig.3).

Properties of the MC as a whole sharply change when its length is changed by a unit, especially by transition from one layer of the residue modulo 2 triangle to another.

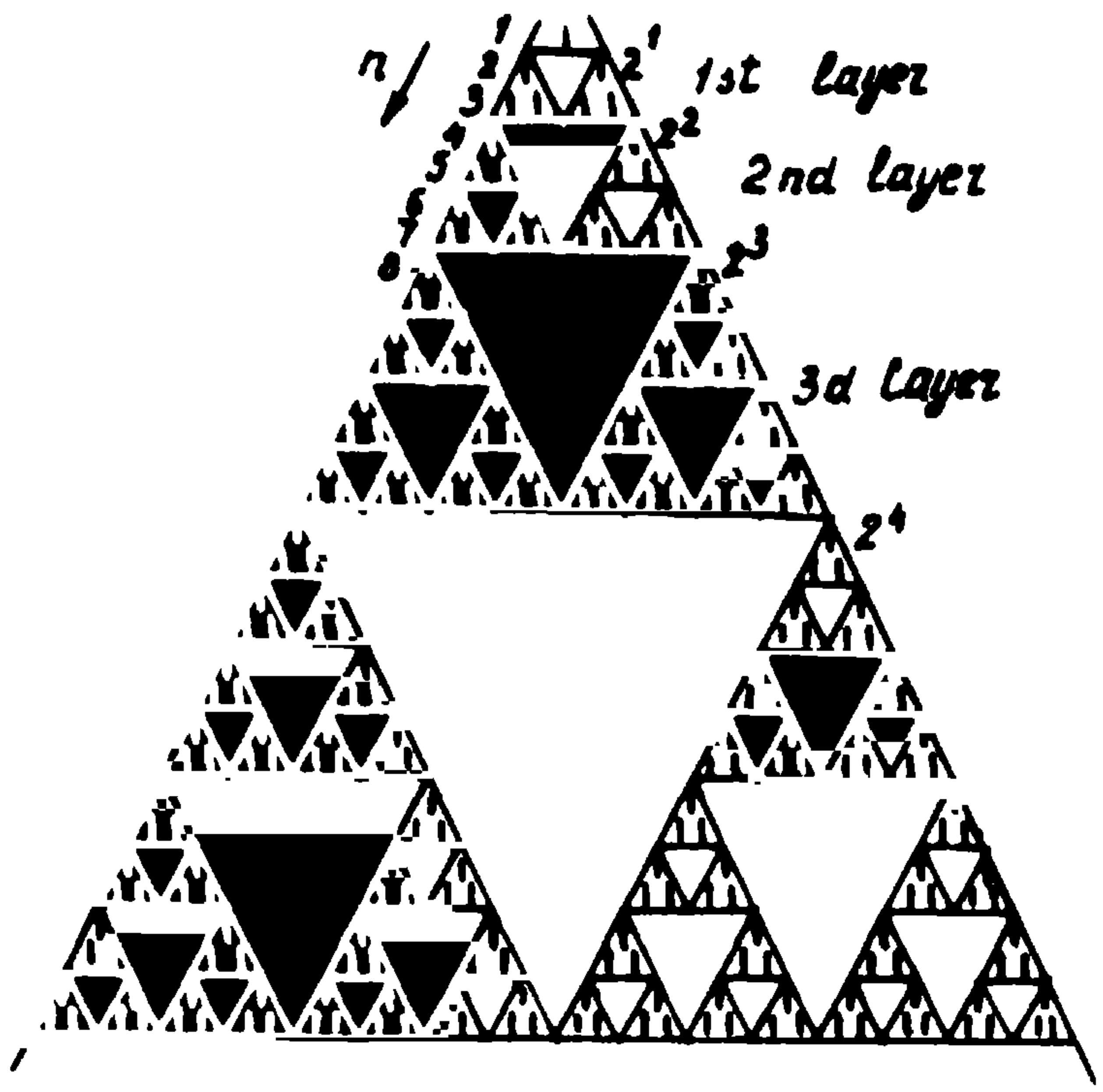


Fig. 3 A residue modulo 2 triangle.

All the input sequences for the MC can be subdivided into two categories (according to transformation in MC character) (Fig.4).non-zero and zero ones. A zero sequence is an input succession which upon entering the input of the MC at a certain moment of time will produce an output succession in a definite number of tacts after this moment consisting of zeroes only (000....0). If a zero sequence (ZS) enters the input of the MC, the information it is bearing will not go further than a certain neuron, in other words, the MC of a definite length appears to be "tuned" to a class of zero sequences, corresponding to its length, the turning being meant as the property of the MC to stem codes of a certain structure. This structure is determined by the number of ranks and the law of one-zero alteration.Thus, in case of the dynamic storage, information of the oDjects which have zero codes corresponding to them does not reach the output of the MC.

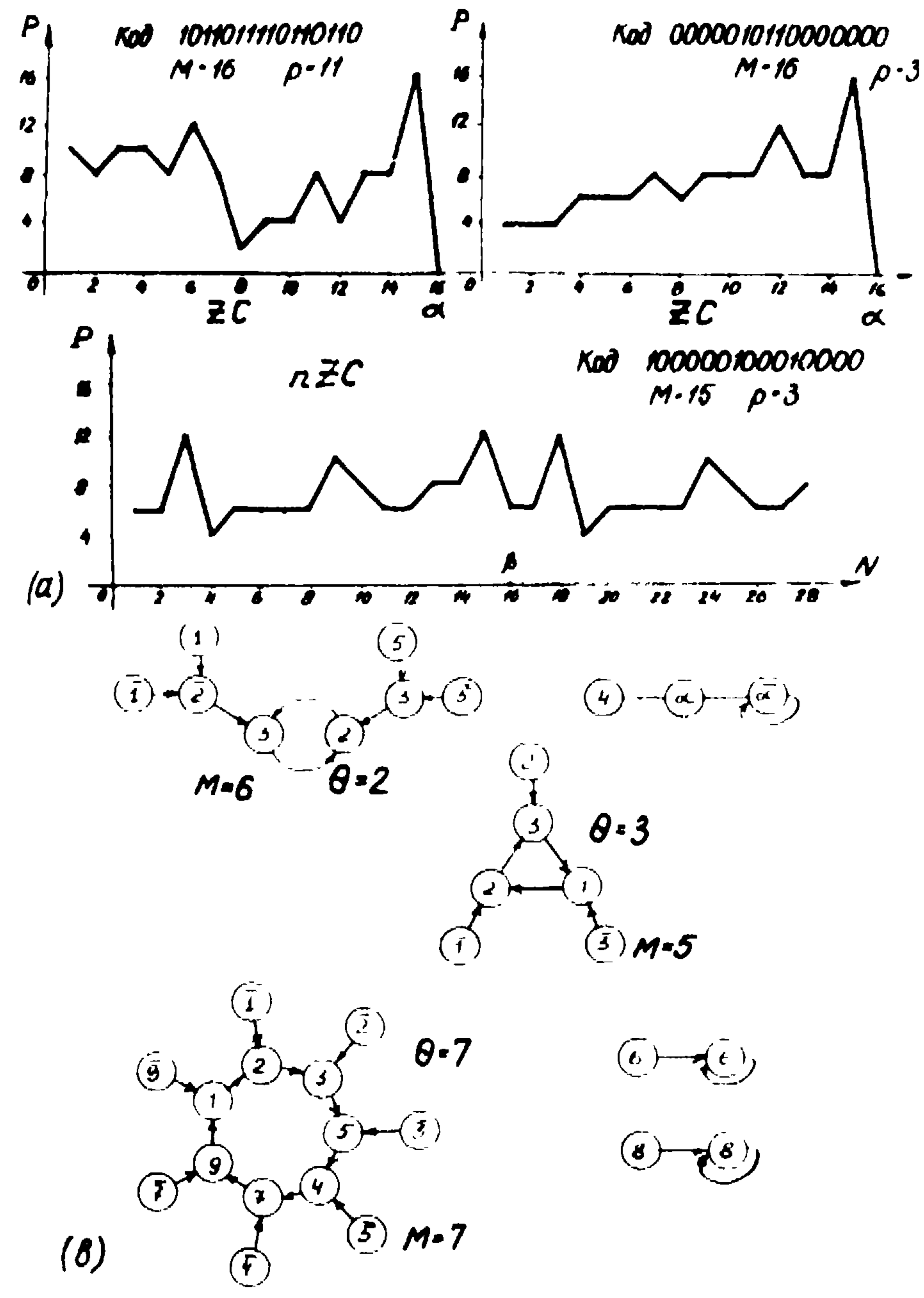


Fig.4 (a) Zero (left) and non-zero (nZC) (right) code transformation dynamic process: M - a quantity of code ranks, P - a quantity of unite in the code, N - a number of chain neurons, (b) Non-zero code transformation dynamic procesB for codes of ranks M=5,6,7.

Zero sequences are a regular system - a converging tree, every apex of which corresponds to one class of the ZS equivalence. One class of the equivalence comprises sequences obtained while tracing one and the same figure, starting points of the tracing being different. Every edge of the tree corresponds to a transformation in one MG neuron of a certain input sequence situated (placed) in the apex, whence the edge issues into a succession on its output situated in the apex where the edge enters. Pig.5 shows a n-rank tree of the ZS (n=8). Layers similar to those in the residue modulo 2 triangle can be distinguished in it. The tree of zero sequence is dichotomous except for borders between layers.

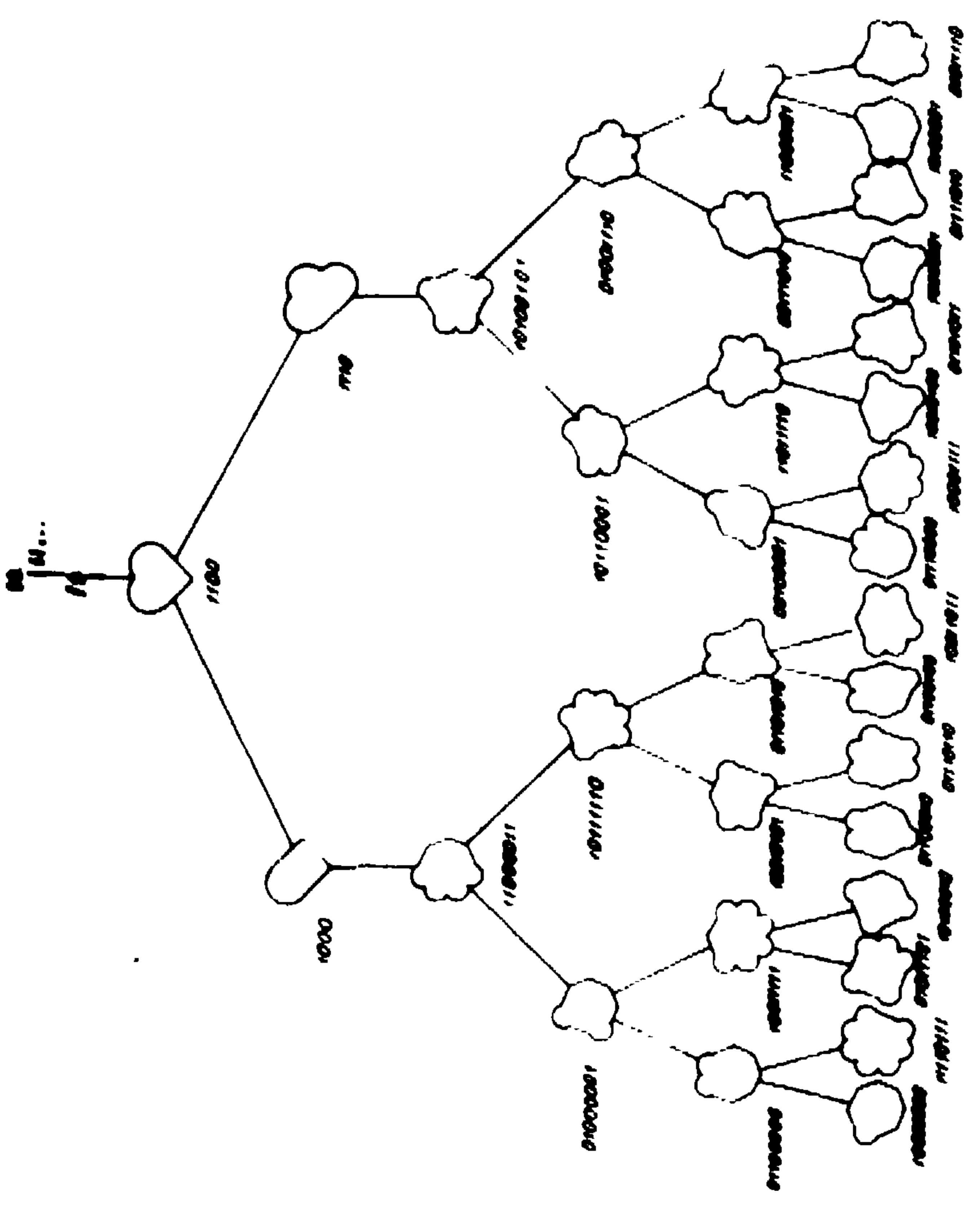


Fig.5 A zero-code transformation tree and corresponding figure transformation tree.

Sequences with equal subperiods are situated in all the apexes of one layer. If one distinguishes three successive layers in the ZS tree, the period of ZSs situated in the upper layer is twice as great as that of ZSs situated in the middle layer.

Movement along the edges of the code tree from a certain apex of the n rank towards the apex of the tree corresponds to the indicated simple transformation of the input sequence situated in this apex during its passage through on-off neurons from the first towards the n one which will have a sequence consisting of zeros only at its output .

If one examines the output sequence of any neuron of the MC the tree of zero sequences will help ascertain what sequence the given sequence will turn into after being transformed on subsequent neurons of the main chain, but there is no direct and simple answer as to transformation of what input sequence results in it. In case input codes with the period not equal to a power of two (non-zero codes) pass through the MG no neuron will yield a sequence consisting of zeros only.

In case input non-zero codes pass through the main chain, a group of successively connected neurons may be picked out of the chain of neurons. A periodic process of code transformation with a period of 0 neurons develops within the group (Fig.4). Number 0 as a characteristic of tne transformation of the input codes essentially depends on the period of the code, not on the type of it, Examples of how various types of the input sequences are transformed are given in figure 4,b.

Transformation of non-zero codes is also a regular system which may be presented as a graph having both cycles and an acyclical part (Pig.4,b).

The knowledge of laws of graph formation enables one to calculate the minimum length of the MC on which the full analysis of the input code signs takes place (code parameters given) and to determine the numbers of the neurons on which the input code appear, which is of importance for the detection and elimination of disturbances in the shape of casual code distortions in the main chain. The main chain may be compared with a set of filters in which the variety of properties of every filter is connected with the number of the corresponding neuron in the chain.

The figures of the same rank may be compared according to the number of connected successively MC neurons in which the non-periodic process of code transformation develops. Let us call this number code the structural characteristic (of the figure) - SC.

Codes with the inner subperiods correspond to figures with periodic properties. The transformation of such codes in the submitted model of SM is characterized by a smaller SC value. Besides this, the shorter the code subperiod (with the rank unchanged), the smaller the SC value. Thus, recording and analysing of a code with inner subperiods in the dynamic and static memory require less time and less structural elements (neurons of the MC and those of the static memory) than the identical processes for the figures with non-periodic properties.

The perculiarity of periodic figure code transformation in the given model of SM may be compared with the perculiarity of perceptron, storage and recognition of the so called "good" figures (Pig.1). These are known to include symmetrical, and, particularly, the figures with periodic properties belonging to "good" ones.

Figures in fig.1,B are divided into "good" (a-d) and "not good" (e-1) in accordance with presence or absence of periodic properties. It takes only one MC neuron and one corresponding group of the static memory neurons for figure a code analyses, two MC neurons for figure b code analyses, three and four MC neurone for polygon c and code analyses but seven-eight MC neurone for polygons e-1 code analyses.

Thus the better the figure the lower its SC value, which results in determining the numerical evaluation of good figure properties.

The process of the passage of the visual object's code through the MC is compared with the storage of information in the dynamic form. Let us assume that before the following sequence arrives the main chain will completely purify. The state of the MC can be characterised by a certain rectangular table, each line of which corresponds to the code at the output of a MC neuron at various moments while a column corresponds to states of the output of MC neurons at one and the same moment. If states of outputs of the initial k-neurons at t_k moment are known, the input code can be restored, i.e., if elements of the k column **($k \leq N$, N -** the length of the MC) are known, the zero line (input sequence) can be determined. Algorithm of the code restoration out of the dynamic storage can be realized by a network consisting of the novelty (H) and the summarizing (Z) neurons. Equations of these types of neurons are shown in fig.6. The elements of MC do not possess memory, and their possessing it is not expedient, since the chain must be purified before introducing the new code. That is why the results of the analyses necessary to the organism in the future, should be transferred from dynamic storing into a static one

Σ	$p(t+1)=1\left[\sum_{i=1}^{n} S_i(t)e_i(t)-m(t)\right]$	$p(t+1)=e_1(t)e_2(t)$ $p(t+1)=e_1(t)\vee e_2(t)$ $p(t+1)=e_1(t)\bar{e}_2(t)$ $n=2$	$p=1\left[\mathfrak{D}\left(\sum_{i=1}^{n} S_i e_i-m\right)\right]$ $S_r e_r \geq m_0$ $1(x)=\begin{cases}1, & x\geq 0\\ 0, & x<0\end{cases}$	$p=\mathfrak{D}(e_1 e_2)$ $p=\mathfrak{D}(e_1\vee e_2)$ $p=\mathfrak{D}(e_1\bar{e}_2)$
on-off	$p(t+1)=1\left[\sum_{i=1}^{n}\lvert S_i(t)e_i(t)-S_i(t-1)e_i(t-1)\rvert-m(t)\right]$	$p(t+1)=e(t-1)\bar{e}(t)\vee\bar{e}(t-1)e(t)$ $n=1$	$p=1\left[\sum_{i=1}^{n}\lvert\mathfrak{D}S_i e_i-\mathfrak{D}^2 S_i e_i\rvert-\mathfrak{D}m\right]$	$p=\mathfrak{D}^2 e\,\mathfrak{D}\bar{e}\vee\mathfrak{D}^2\bar{e}\,\mathfrak{D}e$
on	$p(t+1)=1\left\{\sum_{i=1}^{n}[S_i(t)e_i(t)-S_i(t-1)e_i(t-1)]-m(t)\right\}$	$p(t+1)=\bar{e}(t-1)e(t)$ $n=1$	$p=1\left[\sum_{i=1}^{n}(\mathfrak{D}S_i e_i-\mathfrak{D}^2 S_i e_i)-\mathfrak{D}m\right]$	$p=\mathfrak{D}^2\bar{e}\,\mathfrak{D}e$
off	$p(t+1)=1\left\{\sum_{i=1}^{n}[S_i(t-1)e_i(t-1)-S_i(t)e_i(t)]-m(t)\right\}$	$p(t+1)=e(t-1)\bar{e}(t)$ $n=1$	$p=1\left[\sum_{i=1}^{n}(\mathfrak{D}^2 S_i e_i-\mathfrak{D}S_i e_i)-\mathfrak{D}m\right]$	$p=\mathfrak{D}^2 e\cdot\mathfrak{D}\bar{e}$
H	$p(t+1)=1\left[\sum_{i,j=1}^{n}\lvert S_i(t)e_i(t)-S_j(t)e_j(t)\rvert-m(t)\right]$	$p(t+1)=e_1(t)\bar{e}_2(t)\vee\bar{e}_1(t)e_2(t)$ $n=2$	$p=1\left[\mathfrak{D}\left(\sum_{i,j=1}^{n}\lvert S_i e_i-S_j e_j\rvert-m\right)\right]$	$p=\mathfrak{D}(e_1\bar{e}_2\vee\bar{e}_1 e_2)$
T_p	$p(t+1)=1\left[S_r e_r-m_0-\sum_{i,j=1}^{n}\lvert S_i(t-1)e_i(t-1)-S_j(t-1)e_j(t-1)\rvert\right]$	$p(t+1)=\bar{e}_1(t)\bar{e}_2(t)\vee e_1(t)e_2(t)$ $n=2$	$p=1\left[S_r e_r-m_0-\mathfrak{D}^2\sum_{i=1}^{n}\lvert S_i e_i-S_j e_j\rvert\right]$	$p=\mathfrak{D}^2(e_1 e_2\vee\bar{e}_1\bar{e}_2)$
T_t	$p(t+1)=1\left[S_r e_r-m_0-\sum_{j=1}^{n}\sum_{i=1}^{n}\lvert S_i(t-j)e_i(t-j)-S_i(t-j-1)e_i(t-j-1)\rvert\right]$	$p(t+1)=\bar{e}(t-1)\bar{e}(t)\vee e(t-1)e(t)$	$p=1\left[S_r e_r-m_0-\sum_{j=1}^{n}\sum_{i=1}^{n}\lvert\mathfrak{D}^{j+1}S_i e_i-\mathfrak{D}^{j+2}S_i e_i\rvert\right]$	$p=\mathfrak{D}^2\bar{e}\,\mathfrak{D}\bar{e}\vee\mathfrak{D}^2 e\cdot\mathfrak{D}e$

Fig.6 Different types neurons equations

The model of structure of static storing is a network, consisting of groups of neuron-like elements, equal both in composition and in structure. The number of such groups corresponds to the number of on-off neurons in the chain. Each group has elements to distinguish certain kinds of situations in the input code of the corresponding neuron of MC (indicators), and element accumulating information of the number of repetitions of these situations (counters) fig.2,o. Thus each group analyses the input code of one neuron of MC and stores a certain kind of information of this code, and may be compared with static memory of each element of the structure of dynamic memory.

By code situation we meen a pair of binary symbols corresponding to the values of the neighbouring positions of the code, For analysis and storing in static memory three types of code situations at the input of each on-off neuron of MC are chosen: 1) 00 is the absence of signal difference in the absence of these in the neighbouring measures of time (situation α)- 2) 01 or 10 is signal difference (switch on - switch off type - situation β): 3) absence of signal difference in their presence during the neighbouring measures of time (situation γ).

The code arriving at the input of any neuron of MC arrives simultaneously at the inputs of the three elements of static memory, one of them responding to situation α , the other doing so to β , the third to γ (Fig.2,b). The model of neuron identity in time ($T_t^{\circ\circ}$) reacting only to the absence of signals at its input at two successive instants is used as the first element. The on-off neuron without memory similar to an element of MC is taken as the second element while the model of neuron identity in time T_{tt} responding only to the continuous signal at its input during two successive measures of time is taken as the third one. The output of each of the three described elements, analysing the code situation at the input of some on-off neuron of MC, is bound to the input of the corresponding element-counter (Σ) accumulating and storing information of the number of situations of the given type in the input code of this neuron. Equations of neurons of the types $T_t^{\circ\circ}$, T_t^{11}, Σ are given in the fig.6. Thus the static memory of every neuron of MC includes three analysing elements without memory and three accumulating elements with it.

If we take the static memory of one neuron of MC as an element of the structure of static storing, this structure will be uniform in its original state. While the code of an object passes through MC and undergoes dynamic changes, the structure of static storing becomes non-uniform, while information of code situations is being accumulated. Arrival of the code of the following object will find MC in the same state, as the previous one. But the static memory will be in a rew state by this moment.

Accumulating elements being not uniformly distributed in space corresponds to their being not uniform in time. This absence of uniformity may be observed at the input of each element of the dynamic structure. Presence and measure of this correspondence determines both the very possibility and exactness of restoring of the code of an object by its traces in static memory.

While the code passes through MC, traces of the input code of these elements are imprinted in the static memory of every neuron: elements-counters accumulate and store information of the number of pair-zeroes, pair-units and transitions from zero to unit and from unit to zero. After the code of an object has completely passed through all the neurons of MC, the properties of static memory counters reflect the general number of situations α, β, γ in the former codes; besides this some information of the order of alterations of the three types of code situations is lost in transferring the codes from dynamic into static storing.

This means that identical traces are left by the codes obtained in tracking the contour of one and the same object starting from different points of it, Besides, similar traces in static memory are left by different objects, the codes of which have the same number of situations α, β, γ. The codes of such objects will be called equivalent.

Thus, the algorithm of restoration is essentially recurrent, the maximum number of stages being equal to the number of elements in the main chain. The algorithm of restoration enables one to compare the test code with information in memory with any degree of accuracy which is determined by the chosen number of stages of the algorithm of restoration that are used.