A MODEL OF SELF-ORGANIZATION OF COGNITIVE PROCESSES

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Abstract

The conventional conception of the physiological basis of cognitive processes, which considers the brain only as a neural network, is criticized, and a new conception is proposed. According to this conception, complicated processes in the brain are the result of self-organization of neurons, leading to areas, columns of neurons, etc. Explanation and modeling of different cognitive processes in accordance with this new conception is considered. The possibilities of this approach are demonstrated by explanation of data of thought disorders and modeling of two experimental tasks of visual word perception (lexical decision task and matching of pairs of strings). The architecture of these models is strongly different from the architecture of known connectionist models of visual word perception, although the results of the simulations are comparable to those obtained in experiments with human subjects.

1. Introduction

The usage of neuroscience data for working out new approaches for the explanation and simulation of cognitive processes has always been popular. Parallel distributed processing, or connectionism (McClelland, Rumelhart, et al. 1986) is the latest example of such usage. In this paper we will try to work out a new approach based on data from different areas of neuroscience.

Let us shortly describe the conventional conception of the neurobiological basis of mental processes (Frolov & Murayjev, 1986). According to this conception, the brain is a giant neural network. Neurons are linked by synaptic connections having one direction of synaptic transmission. Synapses only provide access for excitations, but do not play a role in information-processing itself. The discharge of a neuron is the result of the synaptic inputs, and is determined by the summation of the single inputs, and does not depend on specific input signals.

Cognitive processes are considered as the result of spreading of activation through such a network. This conventional conception has provided the physiological basis for several psychological models (McClelland, Rumelhart et al. 1986; Morton, 1969; Rosenblatt, 1961). However, these models, and the conception on which they are
based, do not take into account numerous neuroscience data in an appropriate manner.

Obviously, it is impossible to consider all data available. We shall only consider some aspects relating to different levels of brain organization. For instance, Pribram (Pribram, 1971) considered apical dendrites of cortical pyramidal cells as a continuous structure rather than as a discontinues net. Some authors suggest that the synaptic transmission is not the only way of cellular communication. Electric fields (Pribram, 1971; John, 1982) and diffusion of chemical compounds secreted by some neurons (Roitback, 1975; Schmitt, 1984) have been proposed as the basis of cellular interactions too. There also exist different views on the nature of the processes inside neuron.

For example, interactions between synapses of a neuron based on certain neuromediators may be possible (Kruglikov, 1981), dendrites of a neuron may be excited by electrical fields (Voronkov & Guselninov, 1978). In these cases, a more complex process than the summation of input currencies seems probable. Liberman (1981) assumed that a neuron is a primitive computer rather than a simple threshold element, such that its activity is conditioned both by synaptic influences from other neurons and by its internal program.

2. General Theoretical Framework

The conventional conception does not involve numerous facts, therefore, the description and explanation of complicated processes in the brain (those that could underlie cognitive events) in terms of this conception may be a difficult problem.

We will try to work out a very general approach which allows to describe and, hopefully, explain different brain processes. According to this new point of view, any such process may be considered as a process of self-organization of brain entities. We will not explicitly distinguish all the entities (brain areas, columns of neurons, single neurons, parts of neuron, etc.) as such, as is done in some other approaches. Only the possibility of the determination of entities taking part in particular process is important. Entities of different levels of brain organization may take part in a process of self-organization, thus creating a problem for describing interconnection between self-organization processes at the different levels. However, we will not concern ourselves with this problem in this paper.

We suggest that self-organization is the result of interactions between entities. Interaction between entities leads to change of the states and activity of entities. For example, if a discharge of neuron A exerts an influence on the probability of a spike from neuron B, and vice versa, we can say that neurons A and B interact. We will also say that two entities interact if there is only influence in one direction.
The probability of interaction is estimated by the functional
distance, or alternatively, the functional correlation (FC). The larger
the functional correlation, the bigger the probability of interaction.
For example, if correlation between the electrical brain potentials
(EEG) of two brain areas is significant, it is possible to suppose that
this is the consequence of strong PC between such areas, although the
areas need not be connected by anatomical links. It is difficult to
determine functional correlation in general; there are several possi-
bilities for its evaluation. We consider a few examples below. During
a process of self-organization the functional correlation between
entities may change steadily. The process may be terminated if a
certain distribution of PCs is reached, for instance, if the number of
entities with large PC becomes above than a certain threshold.
Finding a general condition for the termination is a very difficult
problem, therefore these conditions should be determined for each
process separately.

This conception of self-organization may seem very vague,
therefore we demonstrate how two known conceptions can be
translated into the language of our conception. However, we will not
explain or describe physiological evidence for using this conception.
Our objective now is to demonstrate that our conception is
sufficiently general and universal.

First, we will try to translate the conventional theory of processes in
neural networks into our new terminology. Let us for simplicity
consider a discrete process, a generalization should be easy. As entity
we choose a neuron. If neuron A is connected with neuron B through
synapses, the functional correlation between A and B at time-step ;
may be estimated from the absolute value of the product of the
weights of synapses connecting A and B, and the size of the discharge
of neuron A at step i. Similarly, the FC between B and A may be
estimated from the absolute value of the product of the corresponding
synaptic weights and the size of the discharge of neuron B at this step.
The functional correlation between disconnected neurons is always
zero. It is obvious that the distribution of PCs includes information
about the network structure, where PC has a variable value. Common
synaptic transmission is considered as representing the interaction
between the entities concerned, whereas neuron spikes are the result
of all interactions between an entity and another one. Now, it is
possible to describe any process in neural networks in terms of the
terminology of self-organization.

The second example concerns the question how information in the
nervous system is encoded. Some authors have the view that
information is encoded by the frequency of neuron impulses. Other
authors suppose that information is encoded by the pattern of
discharges rather than by the firing frequency of neurons.
(Bechtereva, 1980; Perkel & Bullock, 1969; Vartanian & Pirogov,
According to Vartanian and Pirogov (1988), any neuron is preferably sensitive to a certain pattern of input spike train. After recognizing such a pattern, a neuron discharges its own output pattern, which is the product of an internal program, which in turn is the result of learning. Other patterns lead to random spikes of the neuron. This theory, obviously, suggests that any complicated brain process may be the result of exchanges of the special patterns between neurons. It is not difficult to describe this approach in terms of self-organization of entities, in this case, neurons.

The correspondence between the input and the internal patterns then corresponds to the FC, the pattern transmission from neuron to neuron being the result of their interaction. Now, it is possible to rewrite different ideas of informational pattern theory in our terminology. The translation of different conceptions into the language of self-organization is no problem. The capacity of our conception to mimic other conceptions does not automatically imply that our conception is consistent with the data. But it does allow some intuitive view the brain as a self-organizing system. This is for us a sufficient basis for our further reasoning. The conception of self-organization will be discussed in an article under preparation.

We now consider some psychological consequences of the physiological conception as suggested above. To this end we follow the example of the connectionists. Connectionists describe psychological events as the results of processes in networks with neural-like units. However, the structure of connectionist networks is absolutely different from the structure, for instance, of the human cortex. Also, real neurons have very little similarity to neuron-like units (Reeke, Edelman, 1988). In the same informal manner, we suggest that any cognitive process may be described and explained as a process of self-organization of elements. Both the concept of "psychical object" (letter, word, concept) and elementary process (process of recognition of stimulus, goal-directed movement, procedure, etc.) may correspond to an element. In other words, we do not require any correspondence between physiological process of self-organization process and the cognitive one.

Self-organization is the consequence of parallel interactions between the elements. We suppose that the functional correlation between the elements corresponds to the probability of interaction, increase of the FC leads to the increase of the probability of interaction. Transmission of different patterns of information contained in an element according to different properties of the element, are considered as the result of interactions. Appearances, transformations, and destructions (an element can correspond to a process) of the elements must be the consequences of interactions. As described before, the condition of the termination of interaction is reached when a certain distribution of functional correlations occurs.
Is this fuzzy approach useful? We assume that different cognitive processes may be represented by different parallel self-organizing processes. This view on cognitive processes may lead to new ways for studying and modeling such processes. For instance, connectionism may be "dissolved" in the new approach by following the procedure that was used above to describe neural network processes. The symbol-processing approach may also be represented in terms of self-organization, however, the usefulness of such a representation is still unclear to us, so we will not attempt to describe it here. Of course, the use of the new approach requires some experience: it is necessary to determine elements, rules for the estimation of functional correlation as well as the principles of interactions, the conditions of the termination of the self-organizing process, etc. This new approach may provide more, and new insight compared with the usual approaches.

Let us first consider the well-known example of the connectionist model for the perception of the Necker cube (Feldman, 1985). In this model, each neural-like unit stands for one of two possible representations for each cube node by the visual system, thus the model consists of only 16 units. However, this leads to a problem that each unit, having characteristics of single neuron, should represent the activity of a large group of neurons taking part in the recognition of visual stimuli (John et al., 1986).

It is not difficult to imagine a model for the Necker cube on the basis of the approach given, its sketch may be described as follows: the model also includes 16 elements, but each of them stands for an activity of a large group of neurons without having direct neuron-like characteristics. Instead, the PCs between the elements of one of the representations of the cube are large, whereas the PCs between the elements of different representations are small. The activation of any element results from large PCs between this element and other ones. Such as in the connectionist model, the activation of few elements of one representation can result in the activation of all of the elements of the representation, however now there is not the problem of representation described above. It is necessary to point out this problem exists, for some extent, for many of connectionist models.

2.1. Disorders of Thought

Let an element of the network stand for a concept. Interactions between the elements are determined according to the functional correlation between the two elements, which in turn is evaluated in accordance with the number of common features of the respective concepts. For simplicity it is assumed that the PC must exceed a threshold for an interaction to occur. However, an abstract concept, for example, the concept of animal, includes many concrete concepts. Obviously there must be a threshold for the resemblance of two
features. Such a process is also necessary for a generalization process. If the threshold increases, which may be due to different reasons, then the probability of interactions will change. As a consequence a decline of thought may occur. If the threshold decreases, chaotic, uncontrollable thought may occur. Such phenomena are well-known, for example, in patients with arteriosclerosis or brain damage. If the threshold increases, one may obtain phenomena such as are known of patients in a maniacal state. In a similar manner, but more complicated, one may attempt to explain creative thought or strange, unusual, thought, and schizophrenic thought.

Another example is a phenomenon that is rarely observed in patients who suffer from a disorder of brain circulation (Zeigarnik, 1961, 1976). The patient’s thought is easily affected by load and fatigue. For example, if the patient tries to classify objects pictured on cards, at first he efficiently joins objects into groups by using more generalized dimensions (plants, animals, etc.). A few minutes later however, he stops making the appropriate categorizations, and puts cards together on the basis of seemingly random or primitive features (color, size etc.). After some rest, or after having been attended to the task again, the patient again correctly categorizes the objects.

The conventional explanation of the process of generalization is based on network models (Collins,Loftus, 1975). According to this approach concepts are represented by nodes which are linked to nodes representing categories. Generalization is the consequence of spreading activation in the net. It seems hard to account for the phenomenon of fatigue described, in terms of network models. Why would the nodes and the links corresponding to the abstract level of concepts be disturbed by fatigue?

Our approach suggests that load and/or fatigue affects the threshold of interactions that, in turn, leads to some perturbation of the recursive process of the determination of the functional correlation. The interactions between the nodes of the concrete level are not sufficient for self-organization as needed for the determination of the FC of the nodes at the abstract level. What we then observe is the failure of the system to properly activate the links towards the abstract nodes. This instability must be rare: strong increase of the threshold must entirely destroy thought, whereas weak increase is not noticed. In other words, this phenomenon is the consequence of a weak disorder of brain circulation. After some rest the threshold again decreases, and the usual state of thought is recovered.

3. Modeling some Experimental Tasks Used for the Investigation of Visual Word Perception

Visual word perception is a popular modern area for constructors of connectionist models. Some important connectionist principles have
been developed in this field (McClelland, 1987; McClelland, Rumelhart, 1981; Rumelhart, McClelland, 1982). We consider two models, which we have constructed in the framework of our approach. These models are intended to demonstrate the possibilities of the given approach, rather than to be illustrative of some general theory. It is necessary to point out the two basic differences between the conventional connectionist models and our models.

First, we suggest that complicated processes such as recognition of words or matching of two strings, are based on self-organization of complex patterns of brain activity. It involves spreading of excitation in neural circuits (Bechtereva et al., 1985), rather than activation of neurons in networks with simple structure (see the example with the model of the Necker cube above). Therefore, we will not use the usual connectionist type of architecture: networks with inhibitory and excitatory connections between units and neuron-like units. Instead, a node stands for a pattern of activity itself, each node represents some visual and/or lexical features of a sequence of letters. These features will be described in detail below. In other words, each element may be considered as a container filled with the properties of the sequence of letters. Obviously, such a representation of the complex pattern is rather arbitrary, it is only used for its simplicity, (our objective is the demonstration of the possibilities). It is necessary to point out that some of the nodes (or rather their contents) represent the properties of "real" sequences, such as words stored in long-term memory, whereas other nodes represent the properties of "virtual" sequences, which appear in the process of self-organization. In this process the nodes interact mutually, thereby changing each other's contents. Modified variants of the Hamming distance are used to determine the functional correlation between the nodes. If the FC exceeds a certain threshold, interaction takes place. The elements representing properties of sequences of letters will be called the representative elements. Self-organization of the activity patterns may be understood as a fusion of a large number of local patterns having a sufficient number of properties in common. Therefore, self-organization should terminate when most of the local patterns have merged into the global pattern. In our models, self-organization terminates when a sufficient number of nodes have reached a threshold. We will also say that two elements have a large PC if it exceeds a threshold. The elements with a large FC will be called similar.

Second, the conventional models in fact apply an abstract process of spread of activation in an array of cellular automata, rather than a natural neural process. In our models, however, we want to simulate a natural process. One of the main features of the natural process is that the activity is controlled by purposes and intentions. Visual perception is no exception. The results of experiments in this area are dependent on the experimental tasks used (Besner, McCann, 1987).
We demonstrate our model by means of two experimental tasks: a lexical decision task, and matching of a pair of strings, rather than the abstract process of word recognition. To this end we have put into the models special control nodes that play a role in the process of self-organization, they determine when the process should end. The detailed description of the control nodes for each of the models is given below.

In most conventional models, three levels of different types of nodes occur: a level of features, a level of letters, and a level of words. In our models, there are only two levels of nodes. The nodes at the lower level represent letters in a sequence, its positions in a sequence, and its cases (upper and lower case). The nodes of the upper level represent words and the locations of the letters of the words. Different nodes represent different sequences. The levels interact by exchanging the contents of their nodes.

The processes have been simplified to include only the most essential aspects of visual word perception. This assumption is based on data suggesting the existence of a level of representation of whole words (Henderson, 1987; Rayner, Posnansky, 1978). We suppose that both this level and the lexical level play the most important role in the processes we are concerned with. This role is determined by the experimental tasks simulated. In these experimental tasks there is not the kind of temporal constraint like in tachistoscopic experiments. Consequently the process at the higher, cortical levels probably includes a considerable part of general processing. The models can be extended by adding new lower levels, but this is not to suggest that the number of levels (here two instead of three) is a significant distinction of our model.

In order to construct the model, let us consider the general scheme of processes that take place when a subject performs an experimental task. It is assumed that before stimulus onset, the visual-lexical system preactivates the representative elements and creates the controlling elements, the latter in accordance with the experimental task. There are two sorts of representative elements at each level. The elements of the first kind correspond to words stored in long-term memory. We assume that such elements are not changed in the process of self-organization; they are stable elements (S-elements). The second kind of elements, as emphasized above, are important for processes in the brain leading to creation of an actual image of a stimulus. We assume that such elements can be changed in the process, they are unstable (U-elements). We thus have two types of elements, the minimal number for the model to be sufficiently realistic. With a larger number of types the interactions become very complex. Obviously, most of the elements must be U-elements. The ratio of the number of S-elements to the number of U-elements may be estimated on the basis of physiological data. About half of the neurons of the visual cortex respond to any external stimulus,
whereas 3-5% of neurons change their responses only after learning (Rabinovich, 1975).

We now describe the general scheme. After the stimulus has been presented, the visual information first reaches the U-elements. There occur parallel interactions between the elements. Gradually activation will reach the lexical level, where then a similar process takes place. The lexical level feeds back to the level of elements, while simultaneously input information continues to enter. The controlling elements also exert their influence. The process of self-organization terminates if the number of similar elements reaches a threshold value. The termination means that a perceptive image of stimulus occurred and results in an awareness of the experimental task solution. The models use the simplified scheme: only the internal interactions within the levels are parallel, whereas input information and interactions between the levels occur in turn.

A few words about computational problems. The models were written in Turbo-Pascal, and both letters and cases are encoded by standard Pascal routines. In other words, input information is not introduced by sequence of 0 and 1 as in the connectionist models. Instead, the input is written as strings of letters. The models have only two words, which are stored in 8 S-elements at each level, whereas the number of U-elements is 120 at each level, respectively. Of course, two words are very little, but we think that this is sufficient to demonstrate the possibilities of the models. An increase of the number of words leads to a corresponding increase of the number of U-elements (see the reasoning on the ratio between the two sorts of the elements, above). However, our computational power was very low: most of the simulations were executed on an old, slow PC(AT). The number of words may be changed without changing the programs. The models include a considerable number of parameters (probabilities, coefficients, thresholds, etc.). The parameters were selected according to both the general view on processes, and on our intuition. Doubtless, there is considerable arbitrariness in the parameters (reasons for choosing particular values are described below), nonetheless we observed a curious fact. The models were very robust to change of most of the parameters. Numerous attempts failed to improve the results of the simulations or even to degrade the results by changing some parameters.

3. The Model of a Lexical Decision Task

The first model is concerned with a lexical-decision task. A string is displayed on the screen and remains there until the subject responds by pressing one of two buttons whether the stimulus is a word or not. Obviously, recognition of lexical features is required in this experimental task. Therefore, in the model the controlling elements are supposed to occur only at the lexical level. There are no separate
controlling elements, the control is effectuated by the relevant U-elements of this level. Each of the U-elements includes letters, its positions, and a special label (called lexical meaning) that defines whether the U-element is a word or non-word. Undoubtedly, the controlling elements are very arbitrary, but little is known about the architecture at this level.

The model stores two "words", "joan" and "kitty". Each "word" is represented by four S-elements (two in lower case and two in upper case) at the visual level, and four S-elements at the lexical level.

The simulation begins by assigning to the U-elements random letters and positions. The elements can include missing letters, their positions being zero. At the visual level the case (upper case or lower case) of each letter is chosen randomly. At the lexical level U-elements either contain the lexical meaning corresponding to a word (with probability 0.05), or the one corresponding to a non-word (with probability 0.95). Such an initial predominance of non-words is used to demonstrate the robustness of the model.

Then the model "sees" a string presented and tries to make a lexical decision by acting in accordance with the scheme described above.

At the visual level the simulation proceeds as follows. First, U-elements are chosen with a probability of 0.07, and each subelement (position of letter, letter, letter case) is filled by the corresponding part of the input string with a probability 0.375. This process takes account of the influence from lower levels of the visual system in the general scheme. Such probabilities were chosen in accordance with two principles. On the one hand, we assume that the brain is very chaotic and connections between its parts are sufficiently weak. On the other hand, the simulation must be terminated fast. The simulations demonstrated that the model is robust for variation of these probabilities: the number of the simulation steps could be changed without any remarkable change in the results.

Then the interactions take place, and the functional correlation between two elements is estimated according to the formula

$$ FC = \frac{1.6 * S_0 + 1.3 * S_l + 0.7 * S_c}{N_{isl}} $$

where:
- $N_{isl}$ is the number of input string letters;
- $S_0$ is the number of identical positions in the two elements;
- $S_l$ is the number of identical letters with the same positions in the two elements;
- $S_c$ is the number of identical cases with both the same letters and positions in the two elements.

As was pointed out above, the FC is evaluated according to a variant of Hamming's method for estimating the distance between
two sequences. The coincidences in the elements are computed for the positions of letters which are not bigger than the length of the input string. The coefficients in the formula were chosen on the basis of an obvious assumption: The coincidence of positions is more important than the coincidence of corresponding letters. The results are very sensitive for variations in these coefficients; as a consequence the estimation of the FC is the basis of the process.

If the $FC$ exceeds the threshold (2.86) the elements should be interacted. This threshold was chosen for the coincidences of positions and letters to be sufficient to lead to interaction. If an S-element interacts with a U-element, the contents of the S-element (positions, letters, letters, letter cases) are transmitted to the U-element with a probability 0.95. In other words, the contents of the S-element entirely fill the U-element. Two U-elements interact as follows. An element is randomly chosen as a target, and the other is its source. The contents of the latter are substituted into the former with a probability of 0.875. It is useful to have a higher probability of interaction between S-nodes and U-nodes than between U-nodes. Otherwise self-organization may be impossible, due to random noise. The values of these probabilities only influence the time of the simulation.

The next step of the computation is the calculation of the influence from the visual level onto the lexical level. This influence is computed as follows. The lexical U-elements are chosen as targets with a probability 0.03 (see the assumptions about the connections between the parts of the brain above). Positions and letters of such elements are substituted by those of the random visual elements. The interactions between lexical elements are computed in the same manner as those between the visual elements. The functional correlation is estimated according to the formula:

$$FC = \frac{1.4 \cdot S_o + 1.1 \cdot S_l}{N_{isl}} + LM$$

where $S_o$ and $S_l$; are the same as at the visual level. If both elements have identical lexical meanings, $LM$ equals 1, otherwise zero.

The threshold of interaction is 2.46. If an interaction between an S-element and an U-element occurs, the contents of the S-element are substituted for the contents of the U-element with probability 0.975, lexical U-elements interactions are similar to the visual. One U-element transmits positions, letters, and lexical meaning to the other with a probability of 0.882.

Further, the influence from the lexical level onto the visual level is computed as follows. Visual U-elements receive positions and letters from random lexical elements with a probability 0.015.
For the termination of the process of self-organization we choose the condition that the number of similar elements is at least half of all the elements at each level. However, other conditions for termination are possible. This is a complex problem, whereas the condition chosen has already led to interesting results. Two examples of the lexical decision simulation are given below.

The number of iterations in the simulation is \( L \), \( n \) is the maximal number of similar elements at each level, \( p \) is the ordinal number of the first similar element (all the elements have ordinal numbers in the program), "joan" or "kal l" (the blank reflects a missing symbol) are the contents of this element, and the lexical meaning of such an element at the lexical level is 'word' or 'non-word'.

<table>
<thead>
<tr>
<th>The visual level</th>
<th>The lexical level</th>
</tr>
</thead>
<tbody>
<tr>
<td>( L )</td>
<td>( n )</td>
</tr>
<tr>
<td>2</td>
<td>5</td>
</tr>
<tr>
<td>4</td>
<td>12</td>
</tr>
<tr>
<td>6</td>
<td>32</td>
</tr>
<tr>
<td>8</td>
<td>61</td>
</tr>
<tr>
<td>10</td>
<td>74</td>
</tr>
</tbody>
</table>

Table 1. First example, the input string was "joan".

<table>
<thead>
<tr>
<th>The visual level</th>
<th>The lexical level</th>
</tr>
</thead>
<tbody>
<tr>
<td>( L )</td>
<td>( n )</td>
</tr>
<tr>
<td>2</td>
<td>14</td>
</tr>
<tr>
<td>4</td>
<td>23</td>
</tr>
<tr>
<td>6</td>
<td>16</td>
</tr>
<tr>
<td>8</td>
<td>30</td>
</tr>
<tr>
<td>10</td>
<td>66</td>
</tr>
</tbody>
</table>

Table 2. Second example, the input string was "killl".

It turns out that the model makes a correct lexical decision with respect to recognition of a word or non-word. It is important to note that 95% of the elements have initially random contents; the overall degree of randomization is high in this model.

Often, the lexical decision task has been used to investigate how words or non-words are recognized when account is taken of the visual envelopes. For example, by presenting words or non-words with either lower case or alternating cases. Reaction times and error rates are considered as dependent variables (Besner, McCann, 1987). Such an experiment was simulated with the parameters introduced above. The lower case "words" were ‘joan’ and ‘kitty’, the "words" with alternating cases were 'jOaN' and 'kItTy', the lower case "non-words" were joll, killl, and the mixed "non-words" were JOIL and
Each of the stimuli was "displayed" forty times. The criterion for the termination of self-organization described above was taken as the reaction time. The lexical meaning of the first element from the group at the lexical level was used as the lexical decision. The results are given in Table 3.

<table>
<thead>
<tr>
<th>Stimulus</th>
<th>Dependent variables</th>
<th>Lower case</th>
<th>Alternating case</th>
</tr>
</thead>
<tbody>
<tr>
<td>Word</td>
<td>Reaction time</td>
<td>7,7</td>
<td>9,7</td>
</tr>
<tr>
<td></td>
<td>Error rates %</td>
<td>14,3</td>
<td>35</td>
</tr>
<tr>
<td>Non-word</td>
<td>Reaction time</td>
<td>9,2</td>
<td>10,5</td>
</tr>
<tr>
<td></td>
<td>Error rates %</td>
<td>22,3</td>
<td>15</td>
</tr>
</tbody>
</table>

Table 3. The results of simulation of the lexical decision experiment.

A two-way fixed ANOVA was used for the analysis of the results. "Words" produced faster decision times than "non-words", F(1,156)=5.72, p<0.02, with lower-case stimuli having shorter decision times than mixed words: F(1,156)=10.612, p<0.001. The interaction between the factors is not significant, F<1. It is only significant for error rates, F(1,156)=5.015, p<0.05. A Sheffe test demonstrated that lower case "words" differ from the mixed condition in both reaction time F(1,156)=8.21, p<0.025 and error rates F(1,156)=5.26, p<0.025. There were no such differences for "non-words". In other words, the model demonstrates both word superiority effect and some effect of the distinction between word and non-word with respect to the word envelope (cf. Besner, McCann, 1987).

There is a difference between the results of the simulations and those of human subjects. The size of the interactions between elements in the lexical decision process suggests that due to higher stability of the S-elements than that of the U-elements, the probability of an incorrect decision considered as function of the reaction time must decrease for words and increase for non-words. Therefore incorrect responses must have short latencies for words and long latencies for non-words. In other words, a negative correlation between reaction time and error rates for words and a positive correlation for non-words should be observed. We have conducted a conventional experiment with native Russian speakers to obtain -0.076 as the coefficient of correlation for words, and 0.131 as the correlation for non-words (correct responses were encoded by 0 and incorrect ones by 1). The model yielded positive correlation both for "words" (0.095), and for "nonwords" it was 0.271. It is of interest to compare this model with the connectionist models simulating visual word perception. All the models yield similar results, (by simulating word superiority effect, for example). However, our model can only simulate the type of subject reaction. This leads to a better estimate
for correspondence between the results of the simulations and the "real" experiments.

3.2. The Model for matching pairs of strings

"Same-different" judgment is another experimental task often being used to investigate visual word perception. The experimental task is to match physically simultaneously presented strings of which one is presented above the other:

\[
\text{STRING1} \\
\text{STRING2}
\]


It is suggested that the controlling elements for physical matching are at the visual level. These elements differ, however, from the visual U-elements. There is no information on the elements. Hence the simplest hypothesis that can be used by a subject is that they have no internal structure. Such elements may stand for either a state "same" or a state "different". We assume that such states build up in the visual system in a process of self-organization. The process is based on competition: the dominance of the elements of one state leads to the response in this experimental task. The maximum number of controlling elements that can be built up in our simulation of self-organization is 500.

The S-elements of this model are identical to the S-elements of the lexical decision model. The visual U-elements differ slightly from the U-elements in the first model: there are two input strings in this model, so each U-element contains part of the contents of one of the input strings (the same as those in the first model), and a label (string number) of the input string. It is obvious that there are only two string numbers. The U-elements of the lexical level contain no lexical meaning.

The model stores two words": "anna" and "meggy". Before the onset of the activation levels after input of the strings, the U-elements of the two levels are filled in the same way as in the first model. We tried to use the same parameters in both models; the changes of the parameters are the result of a trial-and-error process rather than of theoretical assumptions.

The simulation is done at the visual level by following the general scheme. The U-elements are chosen with a probability of 0.18 and each part of such elements is substituted by the corresponding part of a random input string with probability 0.006. Moreover, these elements accept their string numbers. The functional correlation is estimated in accordance with the following formula:

\[
FC = \frac{1.4 \cdot So + S_I + 1.1 \cdot Sc}{N_{isl} - \text{max}} + S_n
\]
where \( S_o, S_l, S_c \) are the same as in the first model. \( S_a \) is 0 if both of the string numbers are identical (the string numbers of \( S \)-elements is identical with the string number of any \( U \)-element), otherwise \( S_a \) is 1. \( N_{isl\text{-}max} \) is the maximum number of letters in the input strings.

The interactions of the elements differ from those in the first model. There are two thresholds instead of one. If the functional correlation exceeds the low threshold (2.65), then interaction between the representative elements takes place the same way as in the first model, although the probabilities are different. If an \( S \)-element interacts with a \( U \)-element, the contents (numbers of letters, letters, cases) are transmitted from an \( S \)-element to a \( U \)-element with a probability 0.9, the probability of interaction between two \( U \)-elements is 0.984. During such interaction, the contents of a randomly chosen \( U \)-element are replaced by the contents of the other element. If two \( U \)-elements have different string numbers, and also do not include missing letters, then the controlling element "different" is created in this interaction with probability 0.1. The controlling element "same" can be created with probability 0.1 in interaction between two \( U \)-elements without missing letters if they have the same string number, and if the FC between such elements exceeds 2.725. In other words, 2.725 is the threshold for creating the controlling element "same" in interaction between special \( U \)-elements. Doubtless, the creation of the controlling elements is performed in a rather artificial way. But this method is only the consequence of a long trial-and-error process. All attempts to produce results on the basis of simple, intuitive assumptions have failed.

This influence of the visual level onto the lexical one is computed as follows. Lexical \( U \)-elements are chosen as targets with probability 0.5. The elements receive positions and letters from the visual representative elements, which are chosen randomly. The interactions between the lexical elements are similar as those between the visual elements. The functional correlation is estimated according to the formula:

\[
FC = \frac{1.4 \cdot S_o + 1.1 \cdot S_l}{N_{isl\text{-}max}}
\]

The threshold of interaction is 2.46 at the lexical level. \( S \)-elements transmit letters and their positions with a probability of 0.9. Interaction between two lexical \( U \)-elements takes place in the same manner as between the visual ones, the source substitutes positions and letters for the target with 0.985.

Subsequently the influence of the lexical level onto the visual one is computed as follows: visual \( U \)-elements are chosen with a probability 0.3 and receive letters and their positions from the lexical elements chosen randomly.

The condition for the termination of the simulation is:
- if the identical controlling elements are at least 0.2 of the maximal number of the controlling elements at the visual level,
- the similar elements are at least 0.02 of the representative elements at the lexical level.

This condition is to some extent arbitrary however it is sufficient to obtain interesting results (see the reasoning on the condition of the termination for the first model).

In the simulation the equivalent of reaction times and error rates were determined on the response "different". The pairs of input strings were "meggy" and "mEgGy", "anna" and "aNnA", "ami" and "aNII", and "megli" and "mEgLi". Each of the pairs was "displayed" 25 times.

The number of steps corresponding to the condition of the termination described above was used as the reaction time, the type of the controlling U-elements gaining the highest excitation was used to determine the reaction. The results were as follows:
- mean reaction time for "words" was 13.84,
- mean reaction time for "non-words" was 14.85,
- errors were absent,

The difference between reaction times is significant $t(99)= 2.038$, $p<.05$. In other words, the judgment "different" was done faster for "words" than for "nonwords", which is similar to the results of the experiments with human subjects (Pollatsek, Well, Schindler, 1975). The results of the simulations, however, are not satisfactory. Obviously, we did not discover an effective method for creating the controlling elements. Another method must be discovered, for example matching pairs that are successively presented instead of simultaneously. But it will not be easy to design a connectionist model for that task.

4. Perspectives

We assume that the explanations of thought disorders as well as the two models of visual word perception have demonstrated some possibilities of this approach based on self-organization. Two interconnected directions for the development of this approach seem possible. The first involves verbal explanations and experimental verification for some cognitive processes. The generality of this approach gives a variety of possibilities. The second method is computer simulations. The two simulations described above demonstrate interesting results, in spite of the fact that they are based on a considerable number of arbitrary assumptions, involving a low level of validity. Learning or transformation (learning may be too narrow a concept) is one of the methods for constraining the arbitrariness of the models. For example, any changes in elements of the system that exist after the process has terminated, can be
described as a transformation. Conversion of U-elements into S-elements, if the number of similar U-elements exceeds some threshold, is the simplest example of a learning procedure for the models of visual word perception. Another procedure of transformation seems possible too. These two directions will be the basis for further development of this approach.

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