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Neurodynamic model for creative cognition of relational networks with even cyclic inhibition

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Abstract. The *purpose* of this work is study of the neurodynamic foundations of the creative activity of the brain. Modern AI systems using deep neural network training require large amounts of input data, high computational costs and long training times. On the contrary, the brain can learn from small datasets in no time and, crucially, it is fundamentally creative. *Methods.* The study was carried out through computational experiments with neural networks containing 5 and 7 oscillatory layers (circuits) trained to represent abstract concepts of a certain class of animals. The scheme of neural networks with even cyclic inhibition (ECI networks) contains only bilateral inhibitory connections and consists of two subnets: a reference noncoding network, which is an analogue of the default brain mode neural network, and the main information network that receives time sequences of environmental signals and contextual inputs. After training, the reading of the population phase codes was performed with a simple linear decoder. *Results.* Conceptual learning of the network leads to the generation of a number of spatial abstract images that are distinguished by the most pronounced features of the relevant line of animals. In computational experiments, a wide set of isomorphic representations of concepts was obtained through: a) transformations of image spaces in a wide range of time scales of the training input signal flow, b) internal regulation of the time scales of mental representations of concepts, c) confirmation on the model of the dependence of psychological proximity of concepts on semantic distance; d) calling from memory (decoding) distributed groups of neurons of animal concepts, which the network has not been trained in. *Conclusion.* This paper shows for the first time how, using a small set of event input data (a sequence of 4 CCW and 2 CW signals) and very limited computational resources, ECI networks exhibit creative cognitions based on relational relationships, conceptual learning and generalization of knowledge.

Keywords: conceptual learning, imagination, semantic space, generalization.

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Introduction

In recent years, a new direction of brain sciences has been actively developing — the neuroscience of creative activity. The basis of this direction is the achievements of psychological research in recent decades and the latest results of neurobiological research. It is assumed that the mental mechanisms at the neural network level that support creative thinking and creative cognition arise from the interaction of cognitive processes at a lower level [1]. Creative cognition and creative thinking are complex processes that include components of attention, cognitive control, imagination, generalization and memory [2]. At the same time, the basis of these creative processes is relational thinking, that is, the brain's ability to establish connections between

seemingly unrelated concepts. Various aspects of creative thinking are supported by episodic and semantic memory. Semantic memory provides basic knowledge of facts and concepts that can be combined to solve creative problems and generate new ideas [3], which is confirmed by cognitive and fMRI (Functional magnetic resonance imaging, functional magnetic resonance imaging) studies of semantic memory [4]. Important concepts in theories about the role of semantic memory in creative thinking are conceptual spaces and semantic distance. In recent years, there has been a growing body of evidence for the presence of common neural mechanisms underlying navigation in both physical and semantic space, using in both cases codes of direction and distance between places, even if they are categorical and designated symbols. [5].

The opinion that people can use the same neural mechanisms to support the representation of both spatial and non-spatial information by the organization of concepts and memory using spatial codes has received direct experimental confirmation of the participation of the medial prefrontal cortex and the right entorhinal cortex in this. After training, both regions encoded the distances between concepts, which made it possible to restore an accurate two-dimensional representation of the semantic space directly from their multidimensional activity patterns, while the right entorhinal cortex (EC) demonstrated periodic modulation as a function of the direction traveled. These results show that brain regions and coding schemes that support relationships and movements between spatial locations in mammals are "reused" in the human body to represent a two-dimensional multisensory conceptual space during a symbolic categorization task. [5].

Conceptual knowledge is partially organized into low-dimensional geometries — "cognitive maps which are analogs of world-oriented representations of the environment and are associated with the hippocampal formation of the brain and "image spaces which are analogs of egocentric spatial relationships and are mainly associated with the parietal (parietal) cortex. Cognitive maps are information about distances between locations that were previously shown only in navigation tasks for physical space. The hippocampus encodes in a similar way the distances between points in an abstract semantic space with continuous stimulus signs that were relevant for the acquisition of a new concept [6,7]. Cognitive maps and image spaces may be specific manifestations of the more general tendency of the human brain to organize knowledge in low-dimensional spaces [8]. Image schemes are more abstract than ordinary visual mental images, and consist of dynamic spatial patterns that underlie spatial relationships and movements found in particular real images. Low-dimensional cognitive maps and image spaces play a key role in a person's remarkable ability to draw analogies in different fields. In principle, drawing analogies involves ignoring many differences and focusing on a few similarities between objects. In addition, low-dimensional cognitive maps can be important for creating analogies between objects and events that are far away in our experience, but which can be compared only by a few selected dimensions [8].

Generativity is an ability that is essential for cognitive functions of the brain, including for planning the future, imagination, decision-making and creative activity. Generativity contributes to behavior by predicting future outcomes, which clearly directs current behavior and creativity, and indicates a unified role in cognition. How is generativity implemented in the brain at the neural level, what are the candidate patterns of neural activity encoding a possible future scenario? It has been experimentally established that the hippocampus presents alternative hypothetical scenarios alternately and cyclically approximately every 125 ms, which corresponds to a theta rhythm, that is, the brain simulates all possible behavior scenarios, and not only those implemented in the future! At the same time, the underlying activity patterns had an equivalent temporal structure among different locations and directions of movement, implying a general process of cyclic coding. Moreover, the cycle was started at all levels: from single cells to their populations [9].

In the process of evolution, nature has created organisms capable of diverting their attention from the present moment to create a personal mental space in which an infinite number of possibilities can be realized. The contents of this mental space can take different forms: from

fantasies to re-experiences of a past event or imagining how a future event might unfold. All this is an act of creative thinking, a mental representation of what does not exist at the moment [10]. Note that the definition of "imagination—"imagination" given by the Oxford English Dictionary sounds like "... the ability to form internal images or ideas of objects and situations that are not actually perceived by the senses." What neurodynamic phenomena underlie this ability of the brain is one of the main questions of this study.

Finally, the most important problem of studying creative thinking is understanding the language (code) of thoughts, without which it is impossible to imagine the realization of the huge cognitive potential of the brain. The first broad experimental study of the language of thinking to explain the representation of visual-spatial sequences was conducted by M. Amalric with co-authors [11]. A study of French adults, preschoolers, as well as people from the Amazon Indigenous group — Mundurucu — with limited numerical and geometric vocabulary and access to school education, showed spontaneously occurring primitives of symmetry and rotation. Moreover, the subjects easily combined these geometric forms of primitives into hierarchically organized expressions. The authors' theoretical model suggests that «the subjects 'compressed' spatial sequences into a minimal internal rule or program» [11].

Summing up this review, we briefly note the following. High-level cognitive processing is based on the remarkable ability of the brain to conceptualize information, that is, to distinguish one or more features peculiar to other objects of the environment. These signs correspond to abstract cognitive variables or concepts, the knowledge of which allows you to generalize and immediately draw conclusions about a newly encountered alleged object or event. High-level cognitive processing involves the presence of a language (code) of thoughts, mental compression of perceptual information, flexible recombination of simpler parts, the use of low-dimensional semantic spaces, simple geometric primitives and rules. The language of thinking is based on the brain's ability to establish connections between seemingly unrelated concepts, which determines the relational nature of our thinking. Using the fundamental characteristics of brain activity discussed above, this paper presents for the first time a neurodynamic model of creative cognition of relational neural networks with even cyclic inhibition, including the following series of experiments.

- Investigation of the potential of cognitive capabilities of ECI networks.
- Study of a range of time scales relevant to the generation of abstract images of animals.
- Large-scale transformations of objects by means of internal regulation of the phase timing of events by the contextual input of the network.
- Study of the basics of creative cognition of neural networks with even cyclic inhibition.

The above series of computational experiments are a further development of research on networks with even cyclic braking, see [12, 13]. For the first time, the mathematical model and architecture of these networks were described in detail, indicating dynamic modes, phase transitions demonstrating the genesis of theta-gamma rhythmic activity in the basic module - the main information unit of the network, as well as the basics of phase coding of sensory events in the brain. The next stage in the development of the idea of phase coding in oscillatory networks was its application to the navigational behavior of organisms, where the author's vector-phase and topological approach to computational modeling of this problem was described [14]. An important result of this period of research was the differentiation and functional specialization of information units into topological and directional groupings in each ensemble of the external contours of the network, as well as the gradual transition of ensembles of the internal layers of the network to purely topological ones. This one was first described in the ECI networks model (neural networks with Even Cyclic Inhibition — ECI networks) the neurodynamic phenomenon had an important behavioral functionality: the internal ensembles of the network determined the location of the virtual navigator, the external ones — its spatial trajectory of movement in an allocentric spatial environment [14].

This result is also interesting because the hippocampal cells of the site [15] and entorhinal lattice cells (grids) [16] discovered for the first time in rodents (rats) received their role in a model neural network study at the population level of coding spatial behavior. The reference coordinate system of the ECI network defines a scheme in which spatial information, that is, the position of an object, can be represented relative to the starting point. Depending on the anchoring of the origin of the coordinate system, the same information can be encoded both egocentrically and allocentrically. If the reference system is connected to the navigator's body or a part of his body, for example, the head, then the representation will be egocentric by definition. If the origin is a fixed point of the environment (for example, the corner of the room), then the representation will be allocentric. It is clear that the same spatial information represented by idiotic signals, for example, vestibular, can be used to describe information about one's own movement either egocentrically, that is, relative to the navigator's body or body part, or allocentrically. Together, these types of information give navigating organisms a mental map of the spatial environment that encodes spatial information in allocentric coordinates. [7, 17].

Turning again to the thesis described above that conceptual knowledge is partially organized into low-dimensional geometries - "cognitive maps" that are associated with the hippocampal formation of the brain and "image spaces" we note that the latter definitely belong to the analogues of egocentric spatial relations. We should also add that cognitive maps make it possible to get away from the so-called "curse of dimensionality" problem associated with the fact that objects are characterized by numerous feature spaces, the encoding and recognition of which in a number of life situations would be unacceptably long in time. Therefore, cognitive maps and abstract image spaces may be concrete manifestations of a more general tendency of the human brain to organize knowledge in low-dimensional spaces. It is important that the abstraction process solves this problem by creating abstract variables describing features shared by different concrete objects, reducing dimension and making generalization possible in new situations. [18].

Based on the idea of spatial abstract representations in the mental activity of the brain, the materials of the study of the neurodynamic model of constructing egocentric spatial images of objects are presented here. The result of these studies was the development of a neural code of "thoughts" for learning and spatial representations of a number of objects of living organisms in the form of large-scale symbolic records in the time dimension. A number of modern works emphasize that people can use the same neural mechanism to maintain representations of both spatial and non-spatial information, the organization of concepts and memories using spatial codes. This point of view predicts that the same neural coding schemes that characterize navigation in physical space based on distance and direction should underlie navigation through abstract semantic spaces.

Recently, this point of view has received direct experimental confirmation in the work S. Vigano and M. Piazza [5]. Using the brain's fMRI and representative similarity analysis based on the spotlight model, the authors found evidence of the brain's response to both distance and direction. The areas commonly involved in spatial navigation are the medial prefrontal cortex mPFC and the right entorhinal cortex (EC). After training the study participants, both regions encoded the distances between concepts, which made it possible to restore an accurate two-dimensional representation of the semantic space directly from their multidimensional activity patterns, while the right EC also demonstrated periodic modulation depending on the direction traveled [5]. These results show that brain regions and coding schemes that support relationships and movements between spatial locations in mammals are also used to represent two-dimensional multisensory conceptual space during the symbolic categorization task in humans.

1. Methods

1.1. Spatial organization and mathematical model of networks with even cyclic braking. All experimental series presented in this paper were performed on oscillatory neural networks with even cyclic braking, first described in the works of the author of this article [12, 14]. The ECI network scheme contains only recurrent inhibitory connections and consists of two sub-networks: a reference non-coding, which is an analogue of the Default Mode Network (DMN) – an operational rest neural network, in other words, a passive mode network or a default brain mode network (various translations from English) [4, 19, 20] and the main information network receiving temporary sequences of external information signals and contextual input.

In general, the mathematical model of a freely scalable ECI network looks like this:

$$\begin{cases} \tau_i \frac{dx_i}{dt} = -x_i - b_i z_i - \sum_{j=1}^n a_{ij} y_j + S_{0i} + S_i(t), \\ T_i \frac{dz_i}{dt} = -z_i + y_i, \\ y_i = \begin{cases} k(x_i - p_i), & x_i > p_i, \\ 0, & x_i \leq p_i, \end{cases} \quad i = 1, \dots, N. \end{cases} \quad (1)$$

In particular, its separate module - the oscillator node of the ECI network can be written as the following system of equations:

$$\begin{cases} \tau_1 \frac{dx_1}{dt} = -x_1 - b_1 z_1 - a_{21} y_2 + S_{01}, \\ T_1 \frac{dz_1}{dt} = -z_1 + y_1, \\ \tau_2 \frac{dx_2}{dt} = -x_2 - b_2 z_2 - a_{12} y_1 + S_{02}, \\ T_2 \frac{dz_2}{dt} = -z_2 + y_2, \\ y_{1,2} = \begin{cases} k(x_{1,2} - p_{1,2}), & \text{для } x_{1,2} > p_{1,2}, \\ 0, & \text{для } x_{1,2} \leq p_{1,2}, \end{cases} \end{cases} \quad (2)$$

where x_i – the membrane potentials of neurons; z_i – the depth or degree of adaptation of these neurons to a constant level of input exposure; τ_i – the time constants of the neuron input; T_i , b_i – parameters that determine the time constants and the level of adaptation neurons; p_i – thresholds of neurons; a_{ij} – weights of inhibitory connections; S_{0i} and $S_i(t)$ – constant and variable inputs of neurons, respectively; y_i – output activity of neurons; k – gain; n – number of oscillator nodes of the network.

With certain parameters and ratios of amplitudes of external inputs of neurons, a separate oscillator module is capable of autonomous generation of two rhythms – high-frequency (gamma-like) and slow-wave (theta-like). The generation of these rhythms is triggered by constant, but different levels of excitation and time constants of both neurons, and all phase manipulations with high-frequency oscillation packets are carried out by a short exciting pulse input to a neuron with a small input time constant. A feature of rhythmogenesis in such a module is the presence of various modes of oscillation generation and the existence of phase transitions between them, in particular, from a continuous high-frequency to a two-frequency mode, that is, slow-wave, interspersed with high-frequency oscillation bundles. In such a network, the energy of the input pulse signal patterns leads to phase shifts of high-frequency gamma-ray bursts. Computational experiments show that the phase dynamics of network neurons has a complex dependence on a

number of factors: the state of the network, the energy of input signals, the matrix of weights of inhibitory connections, time constants of inputs and adaptation of neurons. The rhythmogenesis of an individual module is determined by several different factors: a) the difference of the resting potentials of both neurons of the module — S_{0i} ; b) the value of the adaptive parameter of the neuron — b_a ; c) the ratio of the time constants of the inputs of both neurons — τ_i и T_i .

In computational experiments, the solution of the above systems of equations was performed by the 4-order Runge-Kutta numerical method with an integration step equal to 0.01. In all computational experiments, the following numerical values of neuronal parameters for the adaptive neuron module were accepted: $\tau_1 = 0.01$; $T_1 = 30$; $b_1 = 10$; $S_{01} = 0.083$; $\alpha_{12} = \alpha_{21} = 2.27$; for a conditional oscillatory neuron: $\tau_2 = 0.5$; $T_2 = 0.8$; $b_2 = 27$; $S_{02} = 1$; $k = 1$; $p_{1,2} = 0$. All values are — dimensionless. The value of recurrent inhibitory interneuronal connections α_{ij} was a constant value equal to 0.001. The difference between the oscillatory units of the reference and information subnets is only that the information units have external modulating inputs $S_i(t)$, and the reference units do not have such inputs. In all computational experiments, the listed parameters remained unchanged, only the external information inputs changed. The values of inhibitory intramodular connections between adaptive and conditional oscillatory neurons are 2.27, and the weights of network intermodular inhibitory connections are 0.001, that is, they vary greatly. Thus, the functional unit of rhythmogenesis consists of two departments with a significant asymmetry in the setting of their time parameters, high values of intramodule coupling weighting coefficients and a difference in the amplitudes of the constant inputs S_{01} and S_{02} , which affects the dynamic behavior of the oscillator module as a whole, which is characterized by strong nonlinearity. As a result, we emphasize that ECI networks are networks of loosely coupled nonlinear oscillators, which gives greater neurodynamic freedom to the latter. It is also important to note that the reference system of oscillators generating a coherent theta rhythm forms a *in-network time reference system*, which serves to measure the relative phase shifts of the information oscillators, as well as the feed time of the external contextual and information inputs causing these shifts. The external excitatory input of $S_i(t)$ neurons is a combination of a "contextual" input for all units of the network and a specific "differential" input for units with sensitivity to various kinds of network rotations relative to the vertical axis perpendicular to the plane of Fig. 1. These inputs differ in the input time, amplitude and duration of the signals, and this difference was taken into account in the interface with the calculation program.

Combined effects of signals of translational and angular velocity of ECI-network turns lead to modification of phase response curves and their compressed sequential order of representation from the external contour to the internal one in the reference theta cycle. The presence of six steps of local phase coherence in the families of phase curves of networks of any dimension [16] indicates the stability of this neurodynamic phenomenon and is consistent with the conclusion about three directions of spatial symmetry encoded by "lattice" cells of the entorhinal cortex, experimentally confirmed in both animals and humans. Let's explain this conclusion in more detail. A remarkable feature of the entorhinal map, discovered experimentally in rodents (rats), consists in its exceptionally regular organization, with lattices of neighboring cells having a common pitch (the distance between the fields of cell activity) and a common orientation. However, these lattices are spatially displaced, but not rotated relative to each other [16]. Theoretically, if the human brain also includes lattice cells, then our entorhinal cortex as a whole should be more active when we move along the axes of symmetry of our lattices, and less active when crossing these axes in motion. Based on the fact that three such main axes were found in the rat, and that it is possible to move "forward" or "backward" along each of them, which defines six directions, it can be predicted that the activity of the human entorhinal cortex should also correlate with the direction of movement with a 6-fold directional symmetry like this. C. Doeller and co-authors [21] used virtual reality and studied the integral neural activity during the "walking" of the subjects on

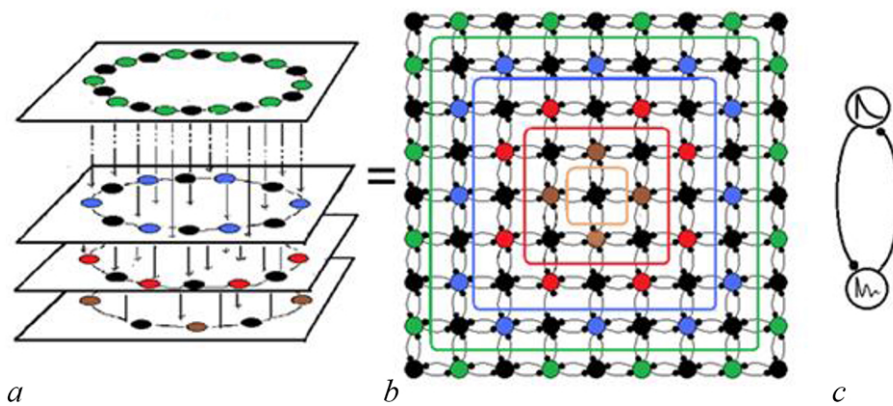


Fig. 1. Пространственная организация многослойных сетей нелинейных осцилляторов с четным циклическим торможением (*a* и *b* — эквивалентные схемы). В любом слое (контуре) сети содержится четное число тормозных связей, отсюда название even cyclic inhibitory networks (ECI-сети). Большими черными кружками обозначены осцилляторные некодирующие модули, образующие референтную систему фазовых отсчетов; большими цветными кружками — информационные осцилляторные модули, на которые поступают внешние возбуждающие входы; малыми черными кружками — тормозные синапсы между осцилляторными модулями. На рис. *c* показан базовый двухкомпарментный элемент, расположенный в узлах решетки ECI-сети — осцилляторный модуль, состоящий из двух нейронов. Вверху — аналоговый адаптивный нейрон с реакцией на ступенчатый вход, показанной внутри нейрона; внизу — условно осцилляторный нейрон с быстро затухающими осцилляциями. Горизонтальные связи между соседними узлами осцилляторной решетки опосредуются между аналоговыми адаптивными нейронами [по 14]. Дальнейшие пояснения в тексте (цвет online)

Fig. 1. Spatial organization of multilayer networks of nonlinear oscillators with even cyclic inhibition (*a* and *b* — equivalent circuits). In any layer (contour) the network contains an even number of inhibitory connections, hence the name even cyclic inhibitory networks (ECI networks). Large black circles indicate oscillatory non-coding modules that form a reference system of phase counts; large colored circles indicate information oscillator modules that receive external exciting inputs; small black circles indicate inhibitory synapses between oscillator modules. Figure *c* shows a basic two-component element located in the nodes of the ECI-network — an oscillator module consisting of two neurons. At the top: an analog adaptive neuron with a step input response shown inside the neuron; at the bottom: a conditionally oscillatory neuron with rapidly decaying oscillations. Horizontal connections between neighboring nodes of the oscillator array are mediated between analog adaptive neurons [14] (color online)

the computer-generated landscape and looked at the areas of the monitor where the activity had a similar pattern described above. It turned out that the human entorhinal cortex really shows this lattice pattern of activity and the corresponding three axes of symmetry in most volunteers.

It has been experimentally shown that mammalian head direction neurons can be controlled by peripheral inputs, mainly vestibular, visual, and auxiliary afferents of the angular velocity of rotation of the head [22–24]. The "spatial view cells" found in primates are characterized by the fact that their activation occurs only when the animal looks at a certain place in space [25, 26]. The highly developed vision and oculomotor system of primates allow them to explore and remember from the outside what is in a particular place of the environment, even without visiting these places. Such spatial review cells can be useful as part of a spatial memory system in which they should provide a representation of a part of space, regardless of exactly where the monkey or man was, and what can be associated with events occurring in these places. Spatial representations of primates should also be useful in memorizing trajectories when performing navigation tasks, etc.

The integral of velocity over time determines the position of the body in space. The same trajectory integration operation is implemented in the hippocampal-entorhinal system of the brain, using signals of the body's own movement during navigation for this operation. In the model under consideration, this implicit trajectory integration operation is implemented as follows. At the input of all information units of the network in the third theta cycle after the start of the integration process, a signal of translational (linear) speed with a duration of 5 cu is received.

time and amplitude increments of $2 \cdot 10^{-5}$ in the range of normalized amplitudes [0.00084...0.0014]. Then, in the next, fourth theta cycle, signals of the angular velocity of rotation are sent to cells sensitive to independent variables — CCW and CW signals with a duration of 3 cu and an amplitude gradient step of $1 \cdot 10^{-5}$ distributed among the relevant cells. All symbolic records of the training datasets presented in this article included various values of relative time intervals between CCW/CW events in a wide range of time scales. An example of an interface with a software package is shown in Fig. 2.

Presented in Fig. 2 the sequence of five numerical values of the training data set, limited to points in the record, means the values of the time intervals between events, and the signals themselves have a standard duration of 3 cu. time. The minus sign in the first inter-event interval means the temporary overlap of the second CCW signal with the first CCW signal by 7 cu in the internal time scale of the neural network, and the value "0" means that the end of the second and the beginning of the third event coincide in time. This form of recording is an expression of a time sequence of signals in the symbolic language of "thoughts" developed by the author — the form of recording, which is shown at the bottom of each graph or diagram presented in the article and which was "understandable" to the trained neural network. The word "understandable" is derived from the word "concept" or "concept hence relational conceptual learning — a neurodynamic learning process of a neural network, as a result of which a network representation of the semantic space of living organisms was obtained. We also emphasize that the combined effects of translational and angular velocity signals on the network in the neurodynamic sense become interdependent, therefore the resulting directions and distances are also interdependent, which is clearly seen in the representations of the spatial trajectories of object images obtained as a result of decoding the population phase curves of information units of the network.

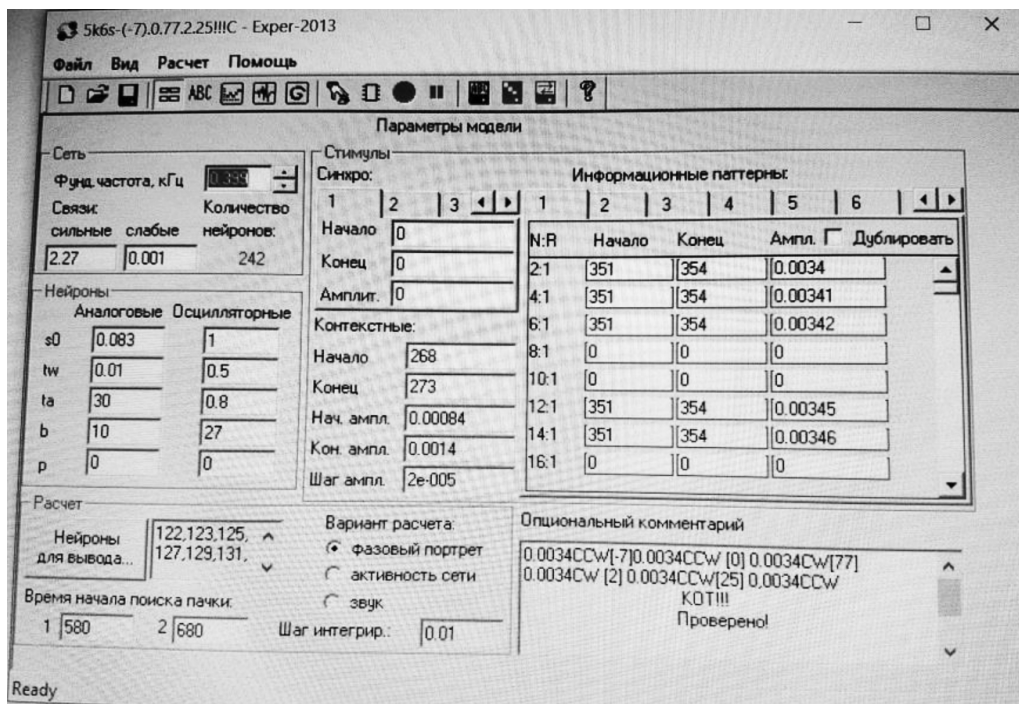


Fig. 2. Снимок с экрана компьютера интерфейс программного комплекса Expert-2013 на примере начала символической записи первого события концепта CAT: 5k6s-[-7].0.77.2.25

Fig. 2. A screenshot of the computer interface of the Expert-2013 software package on the example of the beginning of the symbolic recording of the first event of the CAT concept: 5k6s-[-7].0.77.2.25

1.2. Population phase coding and time compression in the process of network learning. The ECI network scheme, thanks to its symmetrical bilateral organization, can be linked to the "body scheme" of the virtual navigator organism. In particular, if the right diagonal of the neural network structural organization scheme is rigidly connected to the frontal direction of the body, then the right-sided sub-network in the reference system (see below, Fig. 4, shown by the two colors of the cell) will correspond to the right side of the body, and the subcell of cells located to the left of the same diagonal — the left side of the body. To get a complete picture of the neural network's ability to integrate motion trajectories in any direction, namely, in the frontal direction (straight forward), to the right, that is, clockwise (CW), or to the left, counterclockwise (CCW), computational experiments were conducted in which a range of normalized values of amplitudes was determined these directive signals. Integral curves of phase responses of both populations of directionally sensitive network units to CCW and CW signals were constructed by a machine algorithm in consecutive segments in each theta cycle following the signal of the total translational rate.

Patterns of pulse effects of a certain amplitude (in a normalized range of values) and their duration cause a corresponding phase sweep in the theta cycle following the end of the training set. The angular velocity pulse input signal distributed among the relevant inputs of the ECI network is integrated by the network at each step of the amplitude increment of the contextual input of the translational velocity and stored in short-term memory as a rectilinear segment of the phase trajectory - vector, the direction and length of which are represented in two integral families of oppositely directed phase response curves. The entire history of the network's training of an information set of signals in a wide range of time scales is step-by-step compressed and stored in a reference theta cycle following the last theta cycle in which input information was received.

Thus, the entire learning process in ECI networks consists of three time windows: early, medium and late after the input training set is turned on in symbolic form, which is clearly visible on all graphs of phase response curves (Fig. 3, 4, 5). At an early stage of the process, encoding and highly compressed phase implicit representation of both CCW and CW signals in the reference theta cycle occurs. At the second stage, due to the stepwise increment of the amplitude of the contextual input of the translational velocity, orthogonal representations of both angular velocity signals are observed and, finally, their gradual transformation to parallel representations at a late stage of training. At the same time, each step of the modification of the phase representations of the CCW and CW signals under the influence of the contextual input is stored in buffer memory and represented graphically as separate segments of the phase response curves of all information units.

1.3. Representation of the spatial trajectory — the "mental" memory trace of the conceptual representations of the network in the egocentric space. The specific organization of the ECI network encodes the relative spatial order of the fields of activity of information units, and not the dependence of one or another information unit on a specific location or a particular event. It is important that the relative order in the neural network space can be fixed, since the network has local phase coherence and a reference non-coding system of oscillators. Thus, the phenomenon of "perception" of space in this neural network model is based not on a passive reflection of the spatial organization of external stimuli, but on the active construction of one's own internal representation of space. And here the lattice activity of the information units of the network plays an important role, which collectively "sketch" a kind of coordinate grid (like entorhinal lattice fields of activity) on the spatial environment under study. A continuous attractor neural network model can maintain the activity of its neurons to represent

any location along any physical dimension, for example, a visual spatial overview or a given spatial environment. An ECI network can keep a packet of neural activity constant wherever it starts to represent the current state (head direction, position, etc.) [14].

In order to obtain a graphical spatial representation of the motion trajectory, it is necessary to obtain forward phase values at each step of the velocity vector change, which are then translated in accordance with the algorithm described above into segments (rectilinear segments) of the spatial trajectory in an egocentric coordinate system. Thus, the representation of the trajectory occurs in accordance with the vector strategy: the direction and length of each subsequent vector are calculated based on the difference in the phase representations of cells with CW and CCW sensitivity at each step of the increment of the contextual input (the horizontal axis on the graphs of phase response curves). The total time of the process of phase coding and network training in these experimental series was 600–1200 theta cycles with a duration of one theta cycle of approximately 97 cu. time depending on the time scale of the training set of signals (vertical axis on the graphs of phase response curves). The test egocentric space had four fixed directions. Along the horizontal axis, the amplitudes of the contextual input were plotted with the same step as when constructing phase curves; along the vertical axis — the difference between the weighted phase values of CW cells (with a minus sign in the lower half-plane) and CCW cells (with a plus sign in the upper half-plane). This value determined the direction of the motion vector at the current time with accuracy up to a constant coefficient [27].

2. Results and discussion

In the model experiments presented below, a number of results are shown that determine the cognitive neurodynamics of the network, and, in particular, the formation of the conceptual space of the ECI network using the synthesized language (code) of "thoughts". First of all, however, it is necessary to note the neurodynamic similarities and differences of the phase response curves when training each object of this class with training sets of input data (see Fig. 3). Interestingly, the obtained differences in these curves are determined only by the last time interval in the training set, which causes a noticeable restructuring of the entire chain of consecutive segments of the spatial trajectory. Such a coordinated vector-phase rearrangement causes a change in the observed concepts. Another important example of dynamic phase rearrangement, which resulted in a large set of isomorphic concepts of each object, was obtained by reading the code from small distributed groups of neurons with the initial selective CW and CCW tuning (see [28]). Computational experiments were carried out in accordance with the following plan for the study of cognitive neurodynamics of concept representations:

- a) experimental model study of the dependence of the psychological proximity of concepts on semantic distance — a well-known fact in cognitive psychology (see Fig. 3);
- б) studies of the range of time scales of training sets of signals relevant to the generation of spatial representations of animal images (see Fig. 4);
- в) study of large-scale transformations of imaginary objects (see Fig. 5);
- г) study of creative possibilities and demonstration when calling from memory (decoding) animal concepts that the network has not been trained (Fig. 6).

2.1. An experimental study on the ECI-network model of the dependence of the psychological proximity of concepts on semantic distance. The dependence of the psychological proximity of concepts on semantic distance is a well-known fact in cognitive psychology. However, how this problem is solved at the neural network level is not currently known. In this regard, one of the tasks of the present series of model experiments was to search

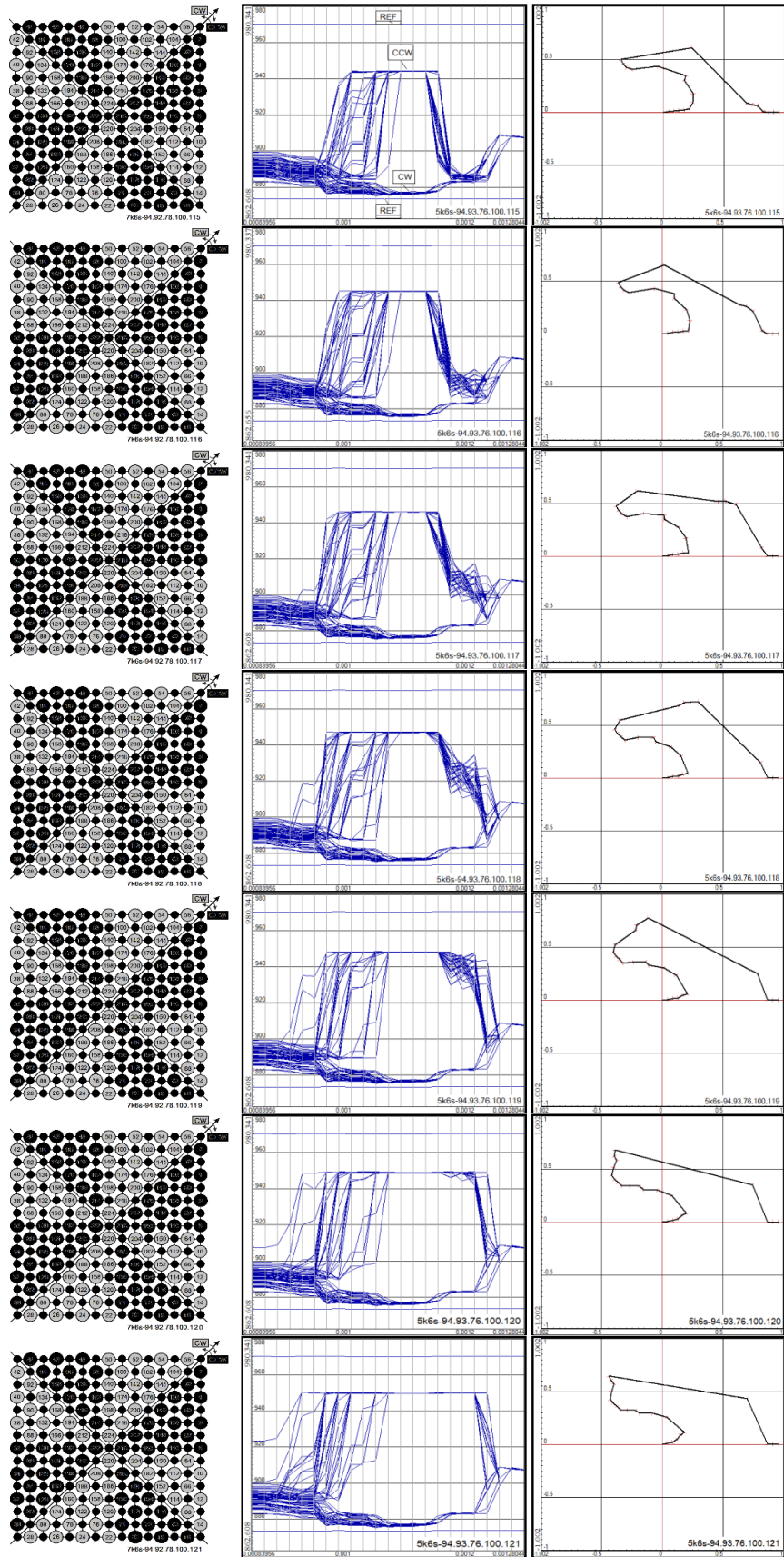


Fig. 3. Семантическое пространство 7 абстрактных изображений животных (сверху вниз: BORZ, DOG, BEA, CAM, BUL, miniBUL и CAT), созданное обучающими входными потоками сигналов, синтезированных автором вручную. Обучающий набор каждого концепта состоит из 6 событий (4 CCW- и 2 CW-сигналов), разделенных временными интервалами различной длительности (здесь и далее показано внизу каждого изображения). В каждом ряду, слева-направо: схема ECI-сети, обученная тому или иному концепту; в центре — кривые фазовых ответов всех нейронов сети в референтном тета-цикле, показанном вдоль оси ординат графиков и обозначенном REF (означающими начало и конец тета-ритма); многочисленные вертикальные линии — шаг градиента контекстного входа, равный $2 \cdot 10^{-5}$; справа — вызов из памяти сети — декодирование популяционного векторно-фазового кода каждого концепта (подробнее см. в работе [12] и ранних работах автора). На схеме сети: большими черными кружками показаны 4 кластера осцилляторных нейронов, чувствительных к вращениям сети против часовой стрелки (CCW), а серым цветом — 4 кластера нейронов — к вращениям по часовой стрелке (CW). Правая диагональ сети, оканчивающаяся стрелкой, привязана к фронтальному направлению схемы тела организма. Решетка малых черных кружков в схеме сети — некодирующая референтная субсеть осцилляторных нейронов. Все связи в сети — билатеральные рекуррентные тормозные; кластеры информационных нейронов, показанные большими черными кружками, получают возбуждающие информационные сигналы с различными временными интервалами и, соответственно, генерируют гамма пачки с различными фазами в тета-цикле. Нейроны схемы, обозначенные малыми черными кружками, получают постоянные входы и генерируют когерентный референтный тета-ритм

Fig. 3. Semantic space of 7 abstract images of animals (top-down: BORZ, DOG, BEA, CAM, BUL, miniBUL and CAT), created by training input signal streams synthesized by the author manually. The training set for each concept consists of 6 events (4 CCW and 2 CW signals), separated by time intervals of different lengths (hereinafter shown at the bottom of each image). In each row, from left to right: an ECI network diagram trained on a particular concept; in the center — curves of phase responses of all neurons in the network in the reference theta cycle, shown along the ordinate axis of the graphs and denoted by REF (meaning the beginning and end of the theta rhythm); numerous vertical lines — the step of the gradient of the contextual input equal to $2 \cdot 10^{-5}$; on the right — a call from the network memory — decoding of the population vector-phase code of each concept (for more details, see [12] and early works of the author). On the network diagram: large black circles show 4 clusters of oscillatory neurons that are sensitive to counterclockwise rotation of the network (CCW), and in gray — 4 clusters of neurons — to clockwise rotation (CW). The right diagonal of the net, ending with an arrow, is tied to the frontal direction of the body diagram of the organism. The lattice of small black circles in the network diagram is a noncoding reference subnetwork of oscillatory neurons. All connections in the network are bilateral recurrent inhibitory; clusters of information neurons, shown by large black circles, receive excitatory information signals at different time intervals and, accordingly, generate gamma bursts with different phases in the theta cycle. Small black circles receive constant inputs and generate a stable reference theta rhythm

for spatial representations of objects (animals) that differ, on the one hand, *the most pronounced signs of relevant animals* (the length and width of the muzzle, the shape of the ears or their absence). On the other hand, in connection with the temporal encoding of input signal patterns that we had previously adopted in studies of the neurodynamics of ECI networks, it was necessary to find a form of symbolic notation in the language of "thoughts" in which the defining variable in the inter-event CW/CCW intervals would be *internal network time*, which determines the spatial representation this or that concept. Recall that the reference subnetwork described in the Methods allows for a highly accurate assessment of time intervals both in the input training sequence of signals and in the time code (relative phase shifts of information units) during network training. In addition, the initial selective tuning of four clusters of information units to incoming input signals counterclockwise (CCW) and the same number with selective tuning to clockwise signals (CW) was adopted. The corresponding settings of the cell clusters are shown in black and gray, and are indicated by the corresponding arrow directions in the upper corner of the ECI network diagram in Fig. 3. In this series of experiments, symbolic recordings of training sets of signals with time intervals of the form 5k6s were used-94.93.76.100.115 — ... 5k6s-94.93.76.100.121 with the last interval successively changing per unit of time, as shown from top to bottom in each row in Fig. 3. The symbolic entries presented here encode a temporary program for supplying input signals to the network, which, ultimately, after decoding the implicit phase representations of the network, allows the observer to see the relative change in the lengths and directions of vectors sequentially constructing the spatial trajectory of an object, starting from the paws and ending with the tail.

It can be seen that as a result of conceptual training of the network and decoding of the population phase code, a series of 7 spatial abstract images was obtained, differing in the most pronounced signs of animals with the conditional names BORZ, DOG, BEA, CAM, BUL, miniBUL and CAT, namely the shape of the muzzle and ears or their absence. Thus, using a minimal set of characteristic features, as a result of this series of computational experiments, a semantic space containing the seven animals listed above was obtained. Each spatial representation of a certain concept from this line of animals is characterized by the total value of inter-event time intervals in the input training sequence. At the same time, the spatial boundaries of particular representations of concepts are due to the difference in the last time interval, which in this case is 1 cu . Note, however, an important detail that the relative representations of concepts do not occur discretely, but continuously (analogically) changing in time dimension, and the difference is 1 cu . It is not a threshold value, but reflects only the most obvious difference between the representations of concepts in the semantic space. In other words, a continuous sequence of spatial representations of objects passes from the most recognizable concepts to the indefinite ones and, returning again, but already to new images from the one presented in Fig. 3 object rulers. In addition, the dependence of the psychological proximity of concepts on the semantic distance, which is observed in this series of experiments described by symbolic records that differ from each other by only 1 cu . The time in the last time interval can be easily extended to other numerous training sets, several examples of which will be discussed in the next section.

In conclusion, we note, in particular, that the DOG concept is clearly perceptually different from the mini bulk concept more than the miniBUL concept from the CAT concept, and this fully corresponds to their distances in semantic space. In the first case, such a distance is 4 cu time, and in the second — 1 cu time, from which it clearly follows that the "driving force" of perceptual differences of objects in semantic space is relative time and related neurodynamic rearrangements in the network. Thus, the concepts BORZ and CAT, located at opposite ends of the semantic line of the category of animals represented by the network, differ in a large amount of relative time. In this regard, we note the opinion of S. Bernardi et al. [18], that the further a person moves away from a concept in the space of semantic memory, the more new or creative this new concept will be.

2.2. Investigation of the range of time scales of training sets relevant to the generation of spatial representations of animal images. The training data set presented above, which differs only in the last time interval, is only one example of the generation of conceptual spatial representations of animals, therefore, the range will be investigated further and the evaluation of time scales relevant to the generation of spatial representations of animal concepts will be given. In addition, the applicability of the above assessment of the perception of perceptual proximity of objects, depending on the semantic distance in the studied range of time scales, will be considered. In the upper two rows of the figure, the time scale of the training dataset of all three DOG, BUL and CAT concepts presented in the symbolic record is 92, 96 and 97 units, respectively, that is, all three time scales of the training signals completely fit into the theta cycle, the duration of which in the model is slightly more than 97 units of time. In the next, 3rd and 4th rows of the same figure, the time scale of the training signal sets of the DOG, BUL and CAT concepts is already 189, 193 and 194 cu ., Nevertheless, the spatial representations of these concepts are perceptually isomorphic to the initial representations in the training sequence of inter-event intervals compressed to a separate theta cycle. Experimental studies of the model have shown a wide range of time scales of training signals up to a tenfold increase. Finally, in the last two rows of Fig. 4 clearly visible distortions of the phase response curves and the corresponding spatial representations of the DOG, BUL and CAT concepts on a time scale, respectively 1060, 1061 and 1063 cu ., are shown, indicating the upper limit of the

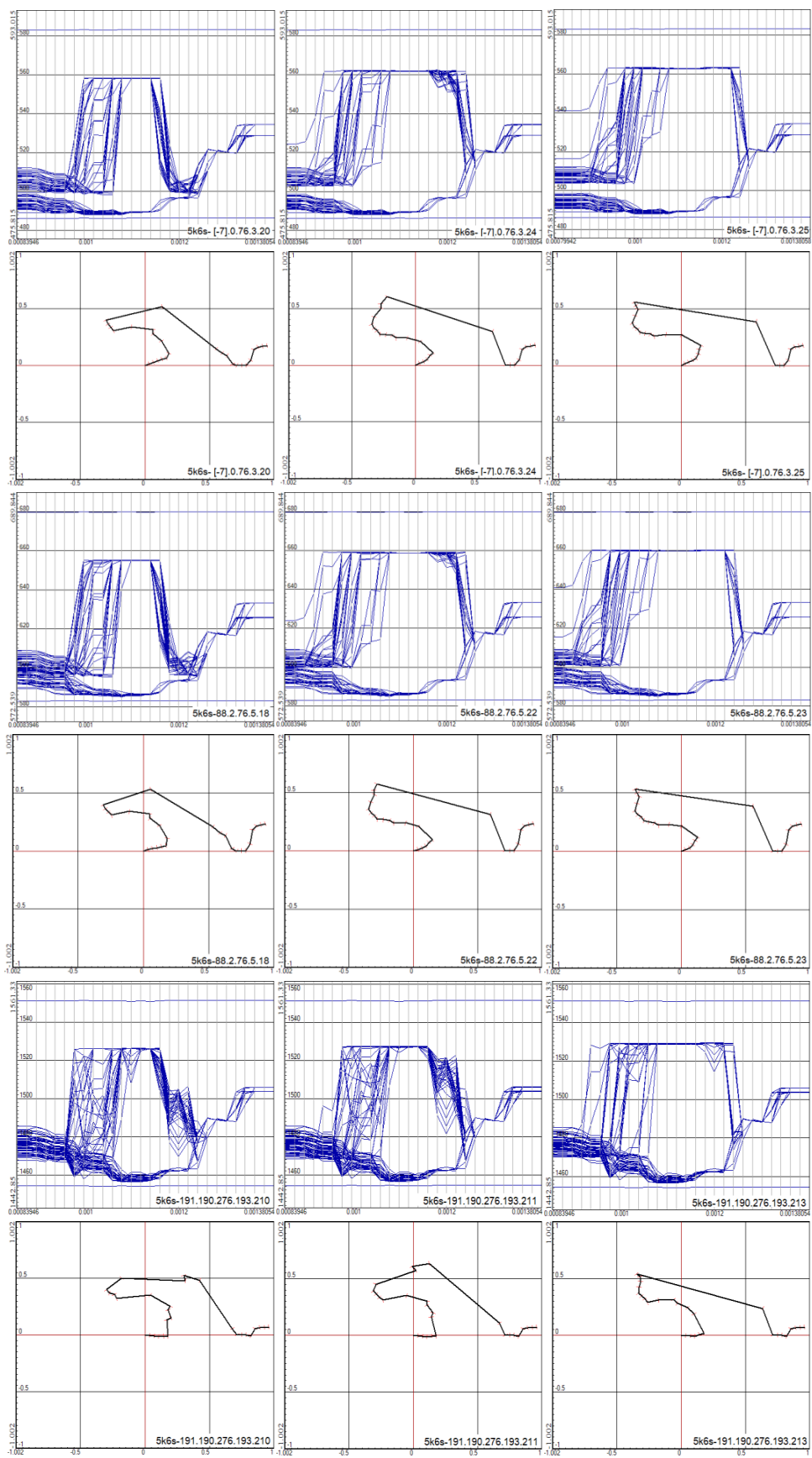


Fig. 4. Концептуальные пространственные представления на примере трёх животных DOG, BUL и CAT в широком диапазоне временных шкал обучающих наборов сигналов, поступающих на информационные входы сети. В первых двух рядах видно, что временные межсобытийные интервалы столь коротки, что суммарно все последовательности сигналов составляют 92, 96 и 97 у.е. времени для трех концептов, соответственно. Знак минус в данном выражении означает перекрытие 1-го и 2-го межсобытийных временных интервалов, а ноль — что между 2-м и 3-м событийными сигналами нет временного разрыва. Во втором случае сумма временных межсобытийных событийных интервалов составляла 189, 193 и 194 у.е., а в последнем — 1060, 1061 и 1063 у.е. Отметьте, что в последнем случае становятся заметны десинхронизированные фазовые кривые информационных единиц, что естественно сказывается на появляющихся искажениях пространственных изображений концептов (нижний ряд)

Fig. 4. Conceptual spatial representations using the example of three animals DOG, BUL and CAT in a wide range of time scales of training sets of signals arriving at the network inputs. In the first two rows of the figure, it can be seen that the time intervals between events are so short that in total all signal sequences are 92, 96, and 97 conventional units time for the three concepts, respectively. The minus sign in this expression means the overlap of the 1-st and 2-nd inter-event time intervals, and zero means that there is no time gap between the 2nd and 3rd event signals. In the second case, the sum of time inter-event event intervals was 189, 193, and 194 conventional time units, and in the latter — 1060, 1061 and 1063 conventional time units. Note that in the latter case, desynchronized curves of phase responses of information units begin to appear, which naturally affects the emerging distortions of spatial images of concepts (bottom row)

range.

It is interesting to note several important results of this series of experiments. Firstly, it is a strict correspondence of each concept to the total value of time intervals attributed to it of a given symbolic sequence of signals. Secondly, the obtained tenfold estimate of the magnitude of the time scale range of the input training signals, relevant to obtaining isomorphic spatial representations of the selected line of animal concepts. Just as the speed of pronunciation of words can vary significantly, but there is a limited physiological range of speeds available for perceptual perception of speech. Thirdly, another proof of the correctness of the methodological approach to modeling cognitive neurodynamics in oscillatory networks with even cyclic inhibition is obtained, expressed in this case in a simple quantitative assessment of the distance between concepts, which reflects the psychological proximity of objects (perceptual similarity) in semantic space: smaller relative distances correspond to greater similarity of spatial representations of animal concepts, smaller similarity — long distances.

In conclusion, we emphasize that the above was achieved despite the fact that the time scale of the input training sets of signals relevant to the generation of spatial representations of animal images was very wide, covering almost a tenfold time range from the upper to the lower limit of the permissible values of the total inter-event time intervals in symbolic records.

In conclusion, we note that the definition of distance provides an internal measure of similarity, taking distance in conceptual space as an indicator of semantic similarity. The concept of similarity is an important construction for modeling categorization and concept formation.

2.3. Regulation of time scales of mental representations of concepts. Understanding how the various objects of our physical environment are interconnected, as well as generalizing this knowledge in different contexts, is one of the fundamental problems of human cognition. Such generalization is a difficult task when relational patterns of input signals are shared in different contexts and presented at different physical scales. This section shows the results of a study of the neurodynamics of different-scale spatial representations of a model performing the task of comparing objects in order to generalize the concepts of "more" or "less" in the context of perceptual perception of "further" or "closer". We emphasize that here we are not talking about comparative amplitudes and time parameters of input information signals about objects (symbolic records about objects remained unchanged).

It is shown here that the general control of the mechanism of temporal flexibility, that is, the control of the variable timing of neurons (in our ECI network model, the control of the

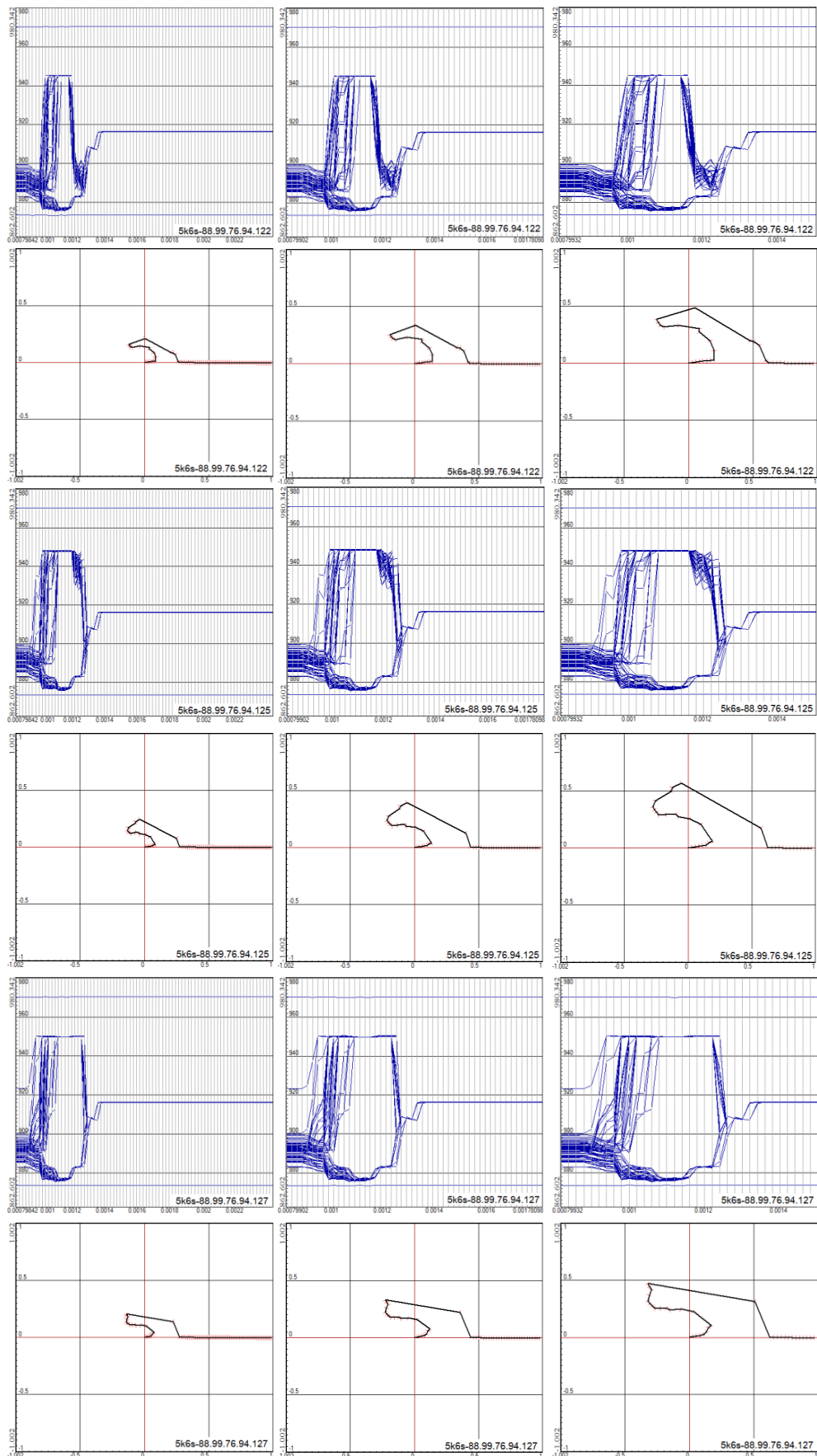


Fig. 5. Внутренние масштабные преобразования пространственных представлений объектов на примере трех концептов, при сохранении во всех трёх случаях амплитуд и межсобытийных временных интервалов внешних входов. Когда в сети устанавливаются более длинные временные интервалы, популяционная активность развивается в соответствии с тем же концептом по инвариантной нейронной траектории, но с меньшей скоростью. Диапазон величин контекстного входа для всех трёх концептов составлял слева направо: [0.0008...0.0024], [0.0008...0.0018], [0.0008...0.0015] с шагом амплитуд $2 \cdot 10^{-5}$ (см. вертикальные линии на графиках кривых фазовых ответов нейронов)

Fig. 5. Internal large-scale transformations of imaginary objects using the example of three concepts, while maintaining in all three cases the amplitudes and inter-event time intervals of external inputs. When longer time intervals are established in the network, population activity develops in accordance with the same concept along an invariant neural trajectory, but at a lower rate. The range of contextual input values for all three concepts was from left to right: [0.0008...0.0024], [0.0008...0.0018], [0.0008...0.0015] with an amplitude step of $2 \cdot 10^{-5}$ (see the vertical lines on the graphs of the phase responses of neurons)

phases of high-frequency bundles in the reference theta cycle), is mediated by a common neural network contextual input. The amplitude of this input determines the total duration of the time interval of the context input, which leads to the modulation of the speed (see Fig. 5). Thus, a modern and reliable conclusion from numerous experiments is that the production of time intervals is mediated by internal temporal scaling of neural signals, that is, contextual signals, regardless of external sensory signals. In the previous section, it was already shown that the network "understands" incoming input signals in a wide range of time scales, which is reflected in numerous isomorphic representations obtained in computational experiments (here shown by the example of three concepts). A fundamental feature of the brain's mental abilities, such as imagination, expectation, and reflection, is that they are not tied directly to sensory or motor events and can unfold on different time scales. Examples of such flexible behavior are managing the coordination of their own movements in athletes or speakers who can control the pace of their speech. People can accurately internally manage the timing of their movements and quickly make changes according to current needs or instructions. To maintain such temporary flexibility, the brain must control the dynamics of current patterns of neural activity, that is, the timing (time) of future movements, adjusting the internal speed command. Thus, cognitive control of internal states can provide a simple and general mechanism for giving temporary flexibility not only to sensorimotor, but also to cognitive functions of the brain. [29, 30].

In recurrent neural network models, time scaling occurs due to non-linearities in the network, and the degree of scaling is controlled by the strength of the external input. Previously, this phenomenon was also established experimentally on animals in accordance with the general principle of time scaling, which was obvious both at the unicellular and population level. In particular, on longer time frames at intervals, the population activity of animals developed along an invariant neural trajectory, but at a slower rate. To investigate the mechanisms underlying such flexible speed control, the authors analyzed the neurodynamics of recurrent networks using gradient input to produce different time intervals. The analysis of these models showed that the degree of scaling was controlled by the input acting on the nonlinear activation function of individual neurons in the network [29].

Similarly, in our model experiments, large-scale transformations of the DOG, BUL and CAT concepts in the context of "further-closer" were obtained as a result of training while maintaining in all three cases the amplitudes and inter-event time intervals of external inputs (see Fig. 5), but population activity developed in accordance with one or another concept along an invariant neural trajectory, but at a slower rate. Thus, large-scale transformations of conceptual representations are implemented *due to changes in the width of the phase window in the reference theta cycle of the network*, determined by the range of values of the contextual input, which physically leads to a spatial representation of the object "further-closer".

2.4. Demonstration of the creative possibilities of relational neural networks with even cyclic braking. The way to understanding the neurocognitive components of creative thinking lies in creating a model that meets certain criteria and quantitative measurements of a number of important characteristics related to the creative activity of the brain, including relational relations of concepts, semantic space of images, semantic distance, large-scale transformations, generation of neural network representations distributed in space and time, the above aspects of which were described and demonstrated in the accompanying figures here and in the previously presented report at the NDKI-2021 conference in Nizhny Novgorod. We emphasize that the neural network mechanisms of creative cognition of the brain remain a fundamental problem, which we will discuss below. It is important that the solution of these problems will be based on a large cognitive and neuroimaging reserve of data, indicating that episodic and semantic memory — memory of autobiographical events and conceptual knowledge, respectively — support various aspects of creative thinking and cognition. It is assumed that semantic memory supports creative thinking, having a knowledge base of facts and concepts that can be combined to solve creative problems and generate new ideas, regardless of time and context [3], whereas episodic memory stores autobiographical memories that depend on time and context [4]. The episodic system is considered constructive: instead of simply reactivating memory tracks in the form in which they were encoded, calling episodic memory involves recombining episodic details to restore a past event. It is believed that these flexible recombinatory processes support episodic thinking about the future — imagining a possible future experience that has not yet occurred — by similarly invoking and combining elements of past experience [34].

How these important theoretical propositions are implemented in our model study is presented in the following series of experiments, where the creative capabilities of an ECI network trained in a single image of an animal are demonstrated by "imagination" (in the absence of external information inputs) of a multitude of abstract representations of concepts (see Fig. 6). In contrast to the previously presented series of experiments, where the directional selectivity of cell clusters marked in black and gray on the network diagram was strictly observed, both during training and decoding when called from memory, in this series of experiments, mixed selectivity of neurons was implemented, in other words, places in "one-color" clusters of network cells when called from memory, they could be replaced by cells with the opposite directionality. Thus, the phenomenon of creative cognition is due to the fact that the "mental imagination" of the network is realized due to the recombination of elements of the event or conceptual features, such as the nose (beak), the shape of the animal's muzzle, passing into the face, etc., etc. From this we can conclude that the expansion of the semantic space of neural network representations is not due to the expansion of the training set of input data (the only input set of signals of the BUL concept was used during training), but due to the internal recombination of image fragments, the use of mixed selectivity of neurons, recruitment when calling from memory distributed groups of information units of the network, which, in turn, increases the level of categorization and, consequently, generalization of mental representations to a wider class of objects, despite the one-time training of the network, as in this example.

The next important attribute that determines the neurodynamics of the creative capabilities of ECI networks is their structural organization, which includes a reference system of non-coding neurons. The functional purpose of this subset of neurons is ambiguous: a) these neurons ensure the stability of the generation modes of networks with positive feedbacks formed as a result of the well-known phenomenon of "inhibition of inhibition"; b) these neurons generate the internal time of the network (clock mechanism) by coherent theta-rhythmic activity, represented on the ordinate axis of the graphs of phase response curves by the beginning and end of the reference theta cycle; c) the range of phases of the phase response curves of all information neurons is

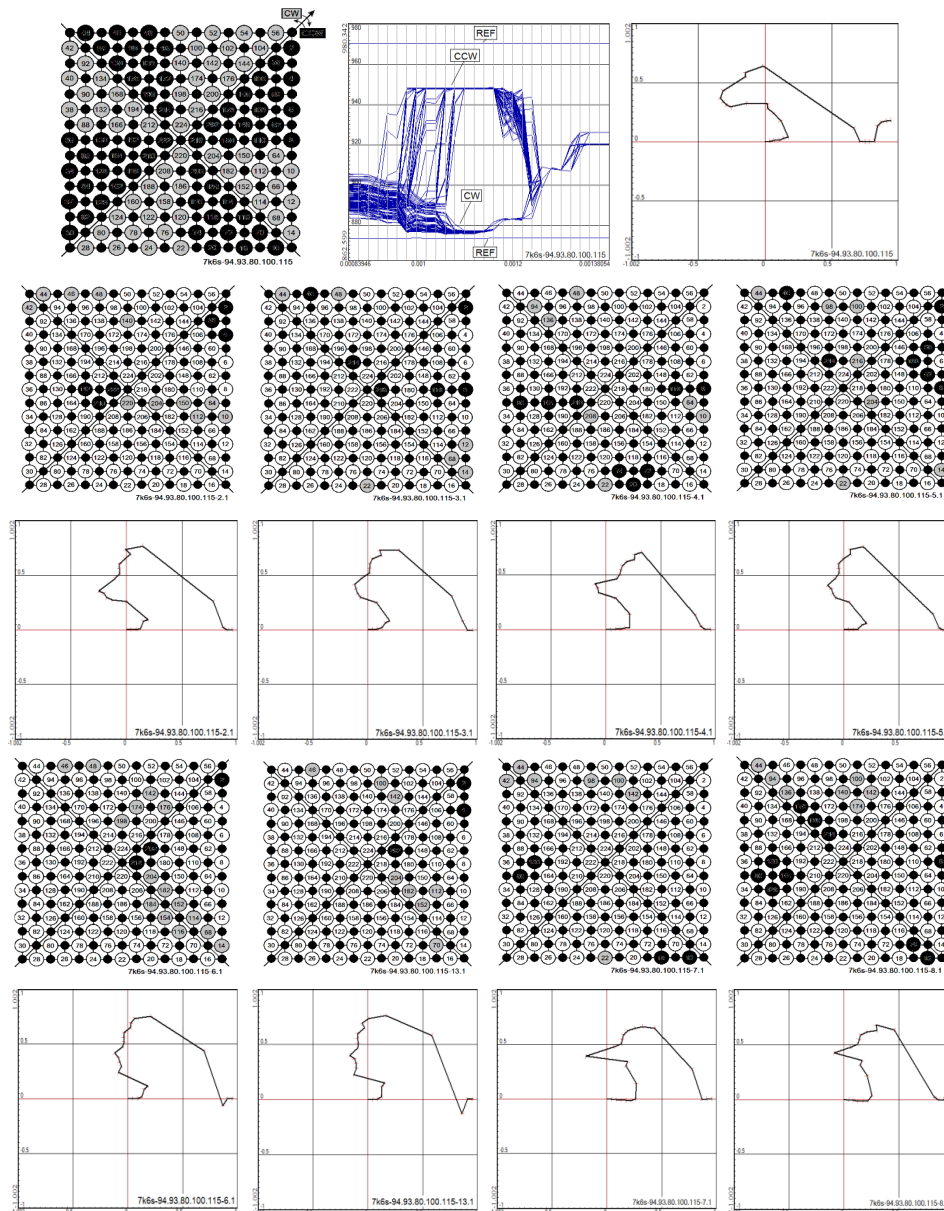


Fig. 6. Воображение многочисленных образов рекрутированием распределенных групп нейронов. Обученная набором данных концепта BUL, 7k ECI-сеть «ментально» представляет различными группами меченных нейронов на схеме сети в 1 и 3 ряду рисунка многочисленные концепты животных, птиц и даже человека (2 и 4 ряд рисунка). Генерация воображаемых образов сетью, обученной единственному концепту BUL, свидетельствует о её способности к обобщениям на целый класс живых организмов, тем самым значительно расширяя собственное семантическое концептуальное пространство. Обратите внимание, что такое расширение семантического пространства произошло из-за нарушения исходной избирательности нейронов к право- и левосторонним поворотам при обучении (см. верхний ряд рисунка) и первые три серии экспериментов, т.е. есть благодаря смешанной селективности при считывании из памяти выделенных групп нейронов

Fig. 6. Imagination of multiple images by recruiting distributed groups of neurons. Trained by the BUL concept dataset (Fig. 1), the 7k ECI network “mentally” represents various groups of labeled neurons on the network diagram in rows 1 and 3 of the figure, numerous concepts of animals, birds, and even humans (rows 2 and 4 of the figure). The generation of imaginary images by a network trained in a single BUL concept testifies to its ability to generalize to a whole class of living organisms, thereby significantly expanding its own semantic conceptual space. Please note that such an expansion of the semantic space occurred due to a violation of the initial selectivity of neurons for right- and left-sided turns during learning (see the top row of the figure) and the first three series of experiments, i.e. due to the mixed selectivity when reading the selected groups of neurons from the memory

limited by the reference theta cycle, regardless of the network dimension (see the example of 5-contour and 7-contour ECI networks; d) this sub-network participates in coordinating access to the semantic knowledge repository, providing the latter with connectivity of neurons in distributed groups.

It is important to emphasize the coordinating role of this neural subnetwork in memory recall, noting that a similar system in the brain was first discovered and described by Marcus Raichle in 2015 [31], having received the names Default Mode Network (DMN) — neural network of operational rest, the default brain mode network (translated from English). In general, numerous studies have shown that the DMC consists of discrete, bilateral and symmetrical regions in the parietal, prefrontal, entorhinal cortex and hippocampus [4, 19, 31, 32]. Extensive and largely overlapping network regions of the default mode participate in the processes of calling episodic and semantic memory of the brain and differ mainly in the different contributions of hippocampal and parahippocampal regions in calling episodic memory [19].

One of the characteristic features of neurodynamics, clearly visible on all graphs of phase response curves, indicates that the patterns of activity of information units were grouped into two synchronized oppositely directed (CCW and CW) clusters. It is assumed that clustering is a geometric structure that allows for an important and clear form of generalization that can be used to determine *when a neural ensemble represents a variable in an abstract format*. This format supports the ability to generalize to new situations. The ability to generalize under new conditions is similar to the ability to decode a variable under experimental conditions that were not used for training [18]. Let us explain this conclusion with our examples. Our linear decoder tracked the phase changes of two opposite clusters of cells at each step of the context change (vertical lines on all phase graphs), producing the resulting spatial representation of the concept that the network was initially trained in (see Fig. 6, top row). Then, under the new conditions of mixed selectivity, the decoder read the phase values of the recruited cells with a changed phase orientation in the theta cycle (that is, offsets to the beginning instead of the end of the theta cycle or vice versa), which as a result represented a new situation for the decoder. Under these conditions, the grouped geometric arrangement of the points of spatial representations of concepts was provided by a successful *generalization of the decoder to new conditions of "mental" experiments*, since the original training data set was aimed at obtaining a single BUL concept.

2.5. Abstract spatial representations of imaginary concepts — internal mental model of generalization of objects. Modern ideas about how new knowledge, imagination and creative thinking are formed are based on two fundamental processes of structuring knowledge in the form of cognitive maps and cognitive graphs. Cognitive maps and cognitive graphs can coexist in the same people, and their availability and use depend on the characteristics of the environment and the target needs of the organism. Cognitive maps and cognitive graphs are created partly by different but partially overlapping neural systems in the hippocampal formation, frontal (frontal) lobes and scene-selective cortical regions. Both representation systems can probably support abstract thinking [7, 17]; cognitive maps are relevant to conceptual representations that change along continuous dimensions, whereas cognitive graphs are— representations of transitions between states and discrete associations between elements [33]. What gives us knowledge of abstract "cognitive" variables or concepts, examples of which were given as a result of the model studies discussed above? Knowledge of abstract variables allows you to generalize and immediately draw conclusions about newly encountered life circumstances. The hippocampus and the entorhinal cortex form relational cognitive maps that contribute not only to episodic memory, but also support the formation of concepts by presenting relevant features for distinguishing related concepts. In addition, the function of memory is not only in remembering important details of individual experience, but also in the ability to link new information between events in order to create new knowledge. Navigation inside hippocampal cognitive maps, which are guided by

lattice hexagonal coding in the entorhinal cortex and implemented by modeling in ECI networks, contributes to the imagination of the concepts presented in this study and further development of research in this direction.

Conclusion

The experimental results indicate a wide variety of abstract conceptual representations obtained in the semantic space of relational neural networks with even cyclic inhibition. It is shown that the phenomenon of creative cognition is due to the fact that the "mental" imagination of these networks is realized due to: a) understanding the language (code) of "thoughts in which the input training sequences were presented; b) the possibility of recombination of elements of conceptual features of objects by recruiting small distributed groups of neurons of the network; c) expansion of semantic space due to mixed selectivity when calling distributed groups of neurons from memory; d) the presence of non-coding, reference neurons in the structure of ECI networks — analogous to the Default Mode Network (DMN) in the brain — performing a unifying role when calling distributed information from memory network units. We also emphasize that the considered model of ECI networks is trained in representations that adapt and compactly capture important details of encoded objects without any semantics built initially into the network architecture. The task of future research is to further develop the creative potential of ECI networks, which includes: 1. Extension of the language of "thoughts" to various classes of physical objects and visual scenes; 2. Combinatorial learning, imagination and understanding of visual scenes, as a consequence of understanding the language of "thoughts in which input training sequences of signals should be presented.

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