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NEURAL-LIKE GROWING NETWORKS IN THE DEVELOPMENT OF GENERAL INTELLIGENCE. NEURAL-LIKE GROWING NETWORKS (P. II)

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Анотація. *Стаття присвячена розробці загального штучного інтелекту на базі нового типу нейронних мереж – «Нейроподібних мереж, що ростуть». Стаття складається із двох частин. Перша частина опублікована в № 4, 2022 р. У першій частині описаний штучний нейроподібний елемент (штучний нейрон) за своїми функціональними можливостями, максимально наближеними до біологічного нейрона. Штучний нейроподібний елемент є основним елементом побудови нейроподібних мереж. У другій частині розглядаються структури та функції штучних і природних нейронних мереж. Пропонується новий підхід до створення нейроподібних мереж, що ростуть, як засіб розробки загального штучного інтелекту максимально наближеної до природного інтелекту людини. Інтелект людини та живих організмів формується їхньою нервовою системою. Основним механізмом вищої нервової діяльності, за визначенням І.П. Павлова, є рефлекторна діяльність нервової системи. У нервовій клітині основним сховищем безумовних рефлексів є молекула дезоксирибонуклеїнової кислоти (ДНК). У статті описано рибосомний синтез білків, що сприяє реалізації безумовних рефлексів та формуванню умовних рефлексів як основи навчання біологічних об'єктів. У першій частині роботи показано, що структура та функції рибосом практично повністю збігаються зі структурою та функціями машини Тюрінга. Тюрінг придумав цю машину для доказу принципової (теоретичної) можливості побудови скільки завгодно складних алгоритмів із гранично простих операцій, причому самі операції виконуються автоматично. Тут виникає приголомшлива аналогія: природа вигадала ДНК і рибосому для побудови складних алгоритмів створення біологічних об'єктів, їх спілкування між собою та з зовнішнім середовищем. Рибосомний синтез білків здійснюється безліччю рибосом. Одночасно зроблений висновок, що нервові клітини мозку являють собою аналогові багатомашинні комплекси – надшвидкодіючі молекулярні суперкомп'ютери з надзвичайно простим аналоговим пристроєм програмування.*

Ключові слова: *природний інтелект, штучний інтелект, нервова система, біологічний нейрон, штучний нейрон, нейроподібний елемент.*

Abstract. *This article is devoted to the development of general artificial intelligence (AGI) based on a new type of neural networks – "neural-like growing networks". It consists of two parts. The first one was published in N4, 2022, and describes an artificial neural-like element (artificial neuron) in terms of its functionality, which is as close as possible to a biological neuron. An artificial neural-like element is the main element in building neural-like growing networks. The second part deals with the structures and functions of artificial and natural neural networks. The paper proposes a new approach for creating neural-like growing networks as a means of developing AGI that is as close as possible to the natural intelligence of a person. The intelligence of man and living organisms is formed by their nervous system. According to I.P. Pavlov's definition, the main mechanism of higher nervous activity is the reflex activity of the nervous system. In the nerve cell, the main storage of unconditioned reflexes is the deoxyribonucleic acid (DNA) molecule. The article describes ribosomal protein synthesis that contributes to the implementation of unconditioned reflexes and the formation of conditioned reflexes as the basis for learning biological objects. The first part of the work shows that the structure and functions of ribosomes almost completely coincide with the structure and functions of the Turing machine. Turing invented this machine to prove the funda-*

mental (theoretical) possibility of constructing arbitrarily complex algorithms from extremely simple operations, and the operations themselves are performed automatically. Here arises a stunning analogy, nature created DNA and the ribosome to build complex algorithms for creating biological objects and their communication with each other and with the external environment, and the ribosomal protein synthesis is carried out by many ribosomes at the same time. It was concluded that the nerve cells of the brain are analog multi-machine complexes – ultra-fast molecular supercomputers with an unusually simple analog programming device.
Keywords: *natural intelligence, artificial intelligence, nervous system, biological neuron, artificial neuron, neural-like element.*

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1. Introduction

An artificial neural network (ANN) is a software or hardware-software implementation of the association of artificial neurons, built on the principle of functioning of biological neural networks. The main most important property of neural networks is that they are not programmed to solve the tasks, but are trained. In the learning process, a neural network can identify complex dependencies between input and output data. The possibility of learning is one of the main advantages of ANN. At the same time, this advantage is also a disadvantage. ANNs require the collection and preparation of large volumes of training samples and time to complete training cycles (epochs). In fact, learning comes down to calculating the optimal coefficients of connections between neurons, which allows for solving the task of classification, recognition, etc. Computer neural networks, which are the basic structure of artificial intelligence (AI) systems, are very popular and successfully solve many different problems.

Artificial intelligence technologies have penetrated all areas of our lives. In 2016, the founder of the World Economic Forum in Davos, Klaus Schwab, called artificial intelligence one of the main driving forces of the fourth industrial revolution. According to modern classification, artificial intelligence is conditionally divided into two classes: general (strong) AI and narrow (weak) AI. General artificial intelligence (AGI) is supposed to be AI comparable to humans, i.e. AI which in terms of development is not inferior to human intelligence and even surpasses it. Weak or narrow AI (Artificial Narrow Intelligence, ANI) shows very weak hints of intelligence and is designed to perform only a strictly defined narrow range of applications. Most modern AI systems allow for achieving remarkable solutions but, as already noted, only for certain tasks.

For example, Deep Blue in chess or AlphaGo in the game of Go, but for other tasks, they require further development or complete reprogramming. To make the AGI technologies, a qualitative transition is needed. Many AI developers are striving to create AGI with capabilities commensurate with the human brain which is the most complex physical object known to mankind. Understanding the laws underlying its functioning is still one of the most important tasks of science. In recent decades, many projects on real-time modeling of brain activity have appeared. These are Human Brain Project, SpiNNaker, SyNAPSE, NeuroGrid, BrainScaleS, etc.

Human Brain Project

One of the largest projects in this area is the Human Brain Project which is being developed in Lausanne by a team of scientists led by Professor Henry Markram. The project aims at achieving a deep understanding of the basics of the functioning of the brain, creating its model inside a supercomputer, and gaining new opportunities in the study and treatment of diseases, as well as in applying the results of the project in the development of artificial intelligence. In 2013, the project received a grant from the European Commission for the amount of 1 billion euros. During the project, the activity of one neural column (an element of the neocortex – a new cerebral cortex) of a rat was modeled on the Blue Gene supercomputer. Currently, Markram is able to model around a hundred similar columns, i.e. the activity of approximately a million neurons. The completion of the experiment is planned for this year, 2023. However, despite the huge investment in projects currently under development, efforts to develop AGI have so far been unsuccessful. Some scientists believe that the creation of AGI will be one of the turning points in human history. This conclusion is based on the fact that if machines can perform a wide range of tasks better than humans, then it will only be a matter of time for them to create even more capable machines. “At this point, it is believed, there will be an “intellectual breakthrough”: machines will improve indefinitely compared to those that were before, and their capabilities will grow in an ever-accelerating stream of recursive self-improvement. It is believed that this process will lead to the emergence of machines with “supermind” [1].

The aim of the paper is to identify the differences between the work of a biological and artificial neural network and to propose a technology for creating a new type of neural networks as a means of developing AGI.

2. Neural networks

In 1943, W. McCulloch and W. Pitts proposed to build a network of artificial neurons, based on the artificial neuron they created, which is a simplified model of a biological nerve cell (the artificial neuron of McCallock and Pitts is discussed in more detail in the first part of this work [2]). In addition, they proved that such a network is capable of learning. In 1949, D. Hebb developed a neural network mechanism and offered the first learning algorithm. In 1958, F. Rosenblatt invented a single-layer perceptron and showed its ability to solve problems of weather forecasting, pattern recognition, and classification. Eleven years later, in 1969, M. Minsky published a formal proof of the limitedness of the perceptron. Subsequent studies conducted by M. Minsky and S. Papert convinced everyone that neural networks have no future. As a result, interest in the development of neural networks has significantly decreased.

A new type of neural networks, proposed in 1973 by T. Kohonen, showed their ability to function as a memory. And in 1974, Paul J. Verbos [3] and A.I. Galushkin [4] simultaneously invented an error backpropagation algorithm for training multilayer perceptrons. By this time, computers with higher processing power appeared. This made it possible to train large neural networks. Interest in neural networks was gradually returning. During that period, systems with a feedback mechanism appeared, learning algorithms were improved and self-learning algorithms were developed. In 1982, J. Hopfield showed that a neural network with feedback loops could be a system minimizing energy. Kohonen presented the models of a network that learned without a teacher, solving problems of clustering and data visualization. By 2000, the development of neurotechnology and the increased power of computers made it possible to realize the most daring AI projects such as control systems, decision-making, recognition, and classification of various objects, etc. Currently, special attention is drawn to the development of intelligent systems using deep neural networks. In 2007, J. Hinton at the University of Toronto created deep learning algorithms for multilayer neural networks using the Restricted Boltzmann Machine (RBM) to train the lower layers of the network.

2.1. Implementations of neural networks

Usually, an artificial neural network (ANN) is implemented in software or hardware and software from a network of artificial neurons and is built on the principle of organization and functioning of biological neural networks.

Let's consider some implementations of ANN. According to the type of connections, ANNs are classified into networks with excitatory connections and networks with inhibitory connections. In addition, as a rule, neural networks have a layered structure and can be single-layer and multilayer. In multilayer networks, neurons are arranged in several layers. The neurons of the first layer receive input signals, transform them and transmit them to the neurons of the second layer. The second layer works similarly, and so on, to the output layer, which produces the output signals.

Single-layer neural networks

The simplest network consists of a group of neurons that form a layer (Fig. 1). Each element from the set of inputs $\boldsymbol{X}$ is connected to each artificial neuron. Each connection has its own weight. The weights are represented by the elements of matrix $\boldsymbol{W}$. The calculation of the output vector $\boldsymbol{N}$, the components of which are the outputs of neurons, is reduced to the multiplication of matrices $\boldsymbol{N} = \boldsymbol{XW}$, where $\boldsymbol{N}$ and $\boldsymbol{X}$ are vector-rows [5].

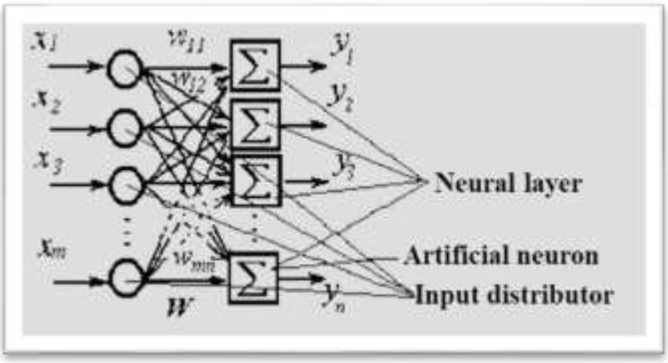

Figure 1 – Single-layer neural network

Multilayer neural networks

Multilayer networks are formed by a sequence of neural layers. The inputs for the next layer are the outputs of the previous layer. In multilayer networks, the output vector of the first layer is calculated by multiplying the input vector by the first weight matrix $\boldsymbol{XW}_1$ and then, if the activation function of neurons is linear, the output vector of the network $(\boldsymbol{XW}_1)\boldsymbol{W}_2$ is determined by multiplying the resulting vector by the weight matrix of the second layer (Fig. 2) [5].

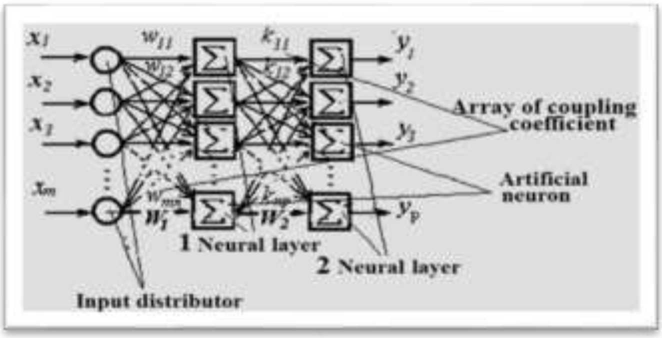

Figure 2 – Two-layer neural network

Direct propagation multilayer networks

Direct propagation networks (perceptrons) consist of several layers of neurons (input layer, hidden layers, and output layer). The outputs of neurons in one layer are connected to the inputs of all neurons in the next layer. The input signal, passing through all layers of the network, is transformed depending on the values of the weight coefficients of connections and the transforming functions of neurons.

Hopfield network

The Hopfield network uses a single-level structure of associative memory (Fig. 3), in which the output vector appears at the output of the same neurons that receive the input vector. The Hopfield network is auto-associative. The input image can be repaired or patched by the network. The Hopfield network is a single layer in which all neurons are interconnected. In the network, each image is stored

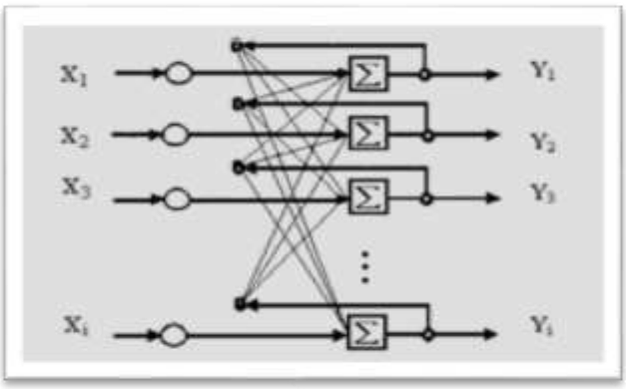

Figure 3 – Hopfield network

through the links between its components. Hopfield introduced the concept of the energy level: $E_0 = 1/2\, Y_t\, (S_t - B_t)$ and made the assumption that the stored images are dynamic attractors (minimizing the energy level), where Y_t is an N-dimensional vector describing the state of the network at time t, S_t is the vector of postsynaptic potential, which is a weighted sum of the outputs of the remaining neurons of the network and the excitation threshold, and B_t is the vector of thresholds.

Kohonen network

Kohonen maps are a two-dimensional array of neurons, with each neuron connected to all input neurons. The first layer distributes the input signal between the neurons of the second layer, located on the plane and interconnected by connections, the strength of which depends on the distance between them, which ensures mutual amplification of the signal by close neurons and weakening by distant neurons. The network defines a spatial neighborhood for each output element. The local neighborhood can be a square, a rectangle, or a circle. The initial size of the neighborhood is usually set in the range from 1/2 to 2/3 of the network size and is reduced according to a certain law (for example, according to an exponentially decreasing dependence). During the training, all weights associated with the winner and its neighboring elements are modified, i.e. for a given input vector, only one neuron goes into an excited state and outputs one, and all the remaining ones are not excited and output zero to the network output. After the neuron is isolated, the weights are adjusted between the first and second layers. The output of each neuron is the sum of the weighted inputs:

$$\boldsymbol{Y}_j = \sum_{i=1}^{n} \boldsymbol{W}_{ij} \boldsymbol{X}_j \,,$$

where $\boldsymbol{Y}_j$ is the output of the j-th neuron, $\boldsymbol{W}_{ij}$ is the weight coefficient of the i-th connection of the j-th neuron, X_i is the input signal coming through the i-th connection, and n is the dimension of the vector $\boldsymbol{X} = (X_1, X_2, \ldots X_n)$. The neuron with the maximum value of $\boldsymbol{Y}_j$ is considered excited. As a result of training the network for a certain number of images, the neurons of the second layer are divided into subsets, each of which corresponds to one of the presented images. The network is successfully used for speech recognition, image processing, robotics, and control problems [6].

ART networks (Artificial Resonance Theory)

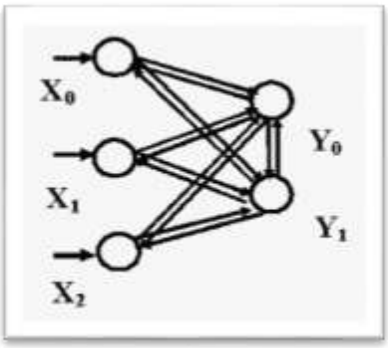

Figure 4 – ART Network

The ART neural network (Fig. 4) models the mechanisms of short-term and long-term memory. The ART network consists of two layers of neurons that implement short-term memory in the form of ensembles of active neurons. Long-term memory is implemented with the help of links going between layers from the bottom to the top and vice versa and their adaptive weights. Features of objects are encoded in the first layer, object classes are encoded in the second layer. Short-term memory is designed to memorize stimuli and classify them, while long-term memory stores information about object classes obtained as a result of training. Various types of ART networks solve the problems of recognizing visual images, processing streams of audio information, and speech recognition [7].

Neural-like networks with an amplification-braking system

Based on the stochastic neuron and the original hypothesis of the amplification-inhibition system proposed by N. Amosov in the early 1960s [8] and developed by his students (E. Kussulem and others), neural networks with an amplification-inhibition system were created. Such neural networks consist of separate neural fields and connections between them. The hypothesis is characterized by two main aspects. The first one is that the main functional unit of the network is a neuronal ensemble. Changes in the activity of the ensemble of neurons are associated with changes in the relevance of the corresponding concepts. The second aspect is that the activity of the neural network is controlled by the amplification-inhibition system. This system identifies the most active ensemble at the moment, increasing its activity, and reduces the activity, i.e. inhibits the others. Subsequently, the effect of the amplification-inhibition system weakens, and at the moment when another ensemble becomes more active, the system switches to it.

Recurrent neural networks that are widely used by neural networks

These networks store the output of a layer and feed it back to the input layer to improve the prediction of the output of a particular layer. Recurrent neural networks have excellent learning opportunities. They are widely used to perform complex tasks such as time series forecasting, handwriting recognition training, and natural speech recognition.

A convolutional neural network is a highly efficient artificial neural network with a unique architecture. The layers in it are organized in three dimensions: width, height, and depth. The neurons in one layer do not connect to all the neurons in the next layer, but only to a small area of the neurons in that layer. The final result is reduced to a single probability score vector ordered by depth in one of the dimensions. Convolutional neural networks are used in areas such as video recognition, image recognition, and recommendation systems.

Generative adversarial networks are regenerative models trained to create realistic content such as images. Each such network consists of two networks known as a generator and a discriminator. Both networks are trained simultaneously. During the training, the generator uses random noise to create new artificial data that looks like real data. The discriminator takes the output of the generator as input and uses the real data to determine if the generated content is real or artificial. Each of the networks competes with the other. The generator attempts to create artificial content that is indistinguishable from the real one, while the discriminator tries to correctly classify the input as either real or artificial. The output is then used to update the weights of both networks to help them better achieve their respective goals. Generative adversarial networks are used to solve problems such as image-to-image conversion and age progression.

Image recognition neural network using logistic map-based kernels (LogNNet)

The neural network uses filters based on the LogNNet logistic mapping. It has a feedforward network structure and the properties of reservoir neural networks. The input weight matrix that is given by the recurrent logistic mapping forms kernels that transform the input space into a multidimensional feature space. The benefit of implementing LogNNet is the significant savings in memory usage. At the same time, LogNNet has a simple algorithm and performance indicators comparable to those of the best resource-efficient algorithms currently available [9].

Deep Neural Networks are artificial neural networks with multiple layers between the input and output layers. A deep neural network finds the correct mathematical transformation method to turn the input into an output, regardless of linear or non-linear correlation. The network moves through the layers, calculating the probability of each exit. Deep neural networks can solve the most complex problems but require significant computing power and large amounts of data.

2.1.1. Training of neural networks

The neural network training process includes the following stages:

1. A problem statement is formulated and a set of key parameters characterizing the subject area is identified.
2. A neural network paradigm (a model that includes the type of input data, threshold function, network structure, and learning algorithms) that is the most suitable for solving this class of problems is selected.
3. A wide set of training examples is prepared and organized as input datasets associated with known output values. The training inputs may be incomplete and partially inconsistent.
4. Training is carried out in accordance with the chosen neural network paradigm and is repeated until the total error in the entire set of input values reaches an acceptable level.
5. The tuned and trained network can be used on real input data, not only suggesting the correct solution to the user but also evaluating the degree of its reliability.

Methods and rules for training neural networks

To determine the learning paradigm, first of all, it is necessary to have a model of the external environment in which the neural network operates, it is necessary to determine how to modify the weight coefficients of connections in the neural network and define which learning rules to use to tune the weights.

There are three learning paradigms: supervised, unsupervised, and mixed. In the case of supervised learning, it is necessary to know the correct answers for each input example. The link weights are adjusted so that the responses received at the output of the network are as close as possible to the known correct responses. Unsupervised learning does not require knowledge of the correct answers to each example of the training sample. In blended learning, part of the weights is determined through supervised learning, while the rest is obtained using self-learning [10].

Usually, in a neural network, in accordance with certain learning rules, the connection weights are adjusted according to the existing training set. Network performance improves as the weights are iteratively tuned.

Thus, the process of training neural networks is reduced to the choice of network architecture and setting the weight coefficients of connections between neural elements.

Methods for training neural networks are developing in two directions: on the ways of interaction with the teacher and on the ways of using the elements of chance. Some scholars distinguish four main types of learning rules: error correction, Boltzmann's rule, Hebb's rule, and competition learning.

Error correction rule

The principle of error correction during training is to use the difference between the values of the desired output and the actual output of the network to modify the weight coefficients of the connections, which ensures a gradual decrease in the error. Various modifications of this learning algorithm are known.

Boltzmann's learning rule represents a stochastic rule. Boltzmann's learning boils down to adjusting the weights so that the states of the visible neurons satisfy the desired probability distribution. Boltzmann learning can be considered a special case of error correction, in which the error is understood as the divergence of state correlations in two modes.

Hebb's learning rule is determined by Hebb's learning postulate. In developing the learning algorithm, Hebb relied on the following neurophysiological observations: if neurons on both sides of the synapse are activated simultaneously and regularly, then the strength of the synaptic connection increases. Hebb's learning rule is formulated in accordance with the following statement: "... if two neurons are simultaneously excited, then it is necessary to increase the coefficients of connections between them." Thus, connections frequently used in the network are reinforced, which corresponds to learning by repetition and habituation. In general, this rule is described as follows:

$$\delta \boldsymbol{W}_{ij} = Cf(\boldsymbol{Y}_i)\, f(\boldsymbol{Y}_j),$$

where $\delta \boldsymbol{W}_{ij}$ is the value of the change in the coupling coefficient $\boldsymbol{W}_{ij}$, $\boldsymbol{Y_i}$ is the level of excitation of the i-neuron, $\boldsymbol{Y}_j$ is the level of excitation of the *j*-neuron, $f(*)$ is a transforming function, and *C* is a constant that determines the learning rate.

The stimulus is the reinforcing rule of learning

The stimulus-reinforcement learning rule is a modification of the Hebb rule, in which, unlike the Hebb's rule, not the activity levels of neural elements are used, but their increments. The operation of the rule is determined by the following expression:

$$\delta \boldsymbol{W}_{ij} = \delta \boldsymbol{X}_i \delta \boldsymbol{U}_{ij},$$

where $\delta \boldsymbol{U}_{ij} = \sum_i \boldsymbol{C}_\tau \,|\boldsymbol{W}_{\tau ij} \delta \boldsymbol{X}_{\tau i}|$, $\boldsymbol{C}_\tau$ is the plasticity constant, $\delta \boldsymbol{U}_{ij}$ is the increment of the potential of the i-th neural element created by j-th neural element for the previous period τ.

Competitive learning

In contrast to Hebbian learning, in which many output neurons can fire simultaneously, in competitive learning, output neurons compete with each other for firing. This phenomenon is known as the winner-take-all rule. During the training, only the weights of the "winning" neuron are modified. Competitive learning allows the clustering of input data. The effect of this rule is achieved by changing the sample stored in the network (the vector of weights of the connections of the winning neuron) in such a way that it becomes a little closer to the input example.

Machine learning is an artificial intelligence technique that allows you to build trainable models for different purposes. There are two types of machine learning: deductive and inductive. Deductive learning is expert systems. In this case, the tasks contain formulated and formalized knowledge. Inductive learning is subdivided into supervised learning, unsupervised learning, active learning, and reinforcement learning.

Of greatest interest is reinforcement learning. Using it, the famous AlphaGo DeepMind beat one of the strongest Go players, Lee Sedol. And the advanced version of AlphaGo Zero surpassed AlphaGo DeepMind in just 40 days of self-learning.

Reinforcement learning (RL) is a machine learning method in which a system (agent) learns by trial and error. The idea is that the agent interacts with the environment, learning in parallel, and receives a reward for performing actions. Reinforcement learning uses a method of positive reward for the right action and negative for the wrong action. Thus, the method assigns positive values to desired actions and negative values to undesired ones. This programs the agent to seek the long-term and maximum total reward in order to reach the optimal solution. These long-term goals do not give the agent the opportunity to stop. Over time, the system learns to avoid negative actions and performs only the positive ones.

RL is a machine learning paradigm able to optimize sequential solutions. It is interesting because it mimics how we, humans, learn things. We can instinctively learn strategies that help us cope with difficult tasks, like riding a bike or taking a math exam. RL tries to replicate this process by interacting with the environment to learn strategies [11].

"Reinforcement learning is a computational approach to understanding and automating goal-driven learning and decision making. It differs from other computational approaches in its emphasis on learning an agent in the process of direct interaction with the environment, without the mediation of a teacher and a complete model of the environment” [12].

Reinforcement learning, although of high potential, can be difficult to deploy and, unfortunately, remains limited in application. One of the obstacles to the deployment of this field of machine learning is the dependence on the study of the environment. As the learning environment becomes more complex, so do the demands on time and computing resources.

Deep learning is a type of machine learning based on artificial neural networks. The learning process is called deep because the structure of artificial neural networks consists of several input, output and hidden layers. Deep learning involves extracting or modeling data features using complex multilayer filters. Since deep learning is a very general modeling technique, it is capable of solving complex problems such as computer vision and natural language processing. This approach is significantly different from both traditional programming and other machine learning methods. Deep learning not only can give results where other methods fail but also allows you to build a more accurate model or reduce the time to create it. This requires large amounts of data for training and large computing power, which is a significant disadvantage. Another disadvantage of deep learning is the difficulty of interpreting the resulting models [13].

Artificial neural networks are used to simulate various brain functions, from face recognition of various objects and images, speech recognition and synthesis, learning, and ending with the prediction of the situation on the stock market. Most models based on artificial neural networks are relatively small in size and limited in functionality compared to real neural networks. And of course, none of them even come close in complexity to the brain. However, in many cases, artificial neural networks perform tasks better than computer programs based on logic and mathematics. Deep learning systems confirm this. Despite the fact that AI based on deep learning remains a black box and at the moment most AI models are not transparent and not explainable – the boom in them continues today. On the other hand, decades of practical applications have shown that deep learning is not the final solution to the problem of creating human-level AI.

2.2. Neural networks of biological objects

The intelligence of man and living organisms is formed by their nervous system (NS). The NS consists of an accumulation of nerve cells (neurons) that form the natural neural networks of the human brain. The structure and functions of a biological neuron are described in the first part of the article [2].

The nervous system is divided into central and peripheral.

Central nervous system (CNS)

The main function of the central nervous system is the implementation of simple and complex reactions of the body which are called reflexes.

In higher animals and humans, the lower and middle sections of the central nervous system – the spinal cord, medulla oblongata, midbrain, diencephalon, and cerebellum – regulate the activity of individual organs and systems of the body, ensure the unity of the body and the integrity of its activity (Fig. 5).

The highest department of the CNS is the cerebral cortex whose different parts regulate the connection and relationship of the organism as a whole with the environment (Fig. 5). The occipital lobe of the cerebral cortex acts as the visual center. There are nerve cells that analyze visual images and recognize lines, geometric shapes, people’s faces, letters, and hieroglyphs – different signals that the visual system supplies. The temporal lobe is the auditory zone. Here comes the information from the cochlea, which has passed through the medulla oblongata and the pons, through the thalamus. There are nerve cells that recognize individual tones or sounds of nature, the splash of water, or the creak of a door. They recognize human laughter and crying, our speech and music. In the front part of the parietal lobe, there is a zone of sensitivity of the body.

There are the neurons that are involved in pain, skin and muscle sensitivity. This is where information comes from the spinal cord through the thalamus. Fig. 6 demonstrates a map of the human body.

Different zones of the body are formed as a reflection of its surface. The leg zone is above everything, then the torso zone is located, then the arm zone, and even lower there is the head zone. Moreover, the head area is not turned upside down, i.e. first goes the forehead, then the upper jaw, lower jaw, and below there is the tongue. The area of the tongue contacts the insula in the lateral sulcus. In the insula, taste centers are located. As a result, for example, sensitivity from the tongue and skin, tactile, temperature, and taste itself are collected inside the lateral groove into a single taste image (Fig. 6). The back of the frontal lobe is responsible for movement. This is the premotor and motor cortex, where voluntary movements are generated, which are defined as new movements in new conditions. It is from this area that signals enter the cerebellum and basal ganglia so that they remember new motor programs. The back of the parietal lobe and the anterior part of the frontal lobe are the higher mental centers. The associative parietal cortex is connected, first of all, with our thinking and work with words. And the associative frontal lobe or prefrontal cortex is the center of will, initiative, and decision-making. The choice of behavioral programs and their launch are made here.

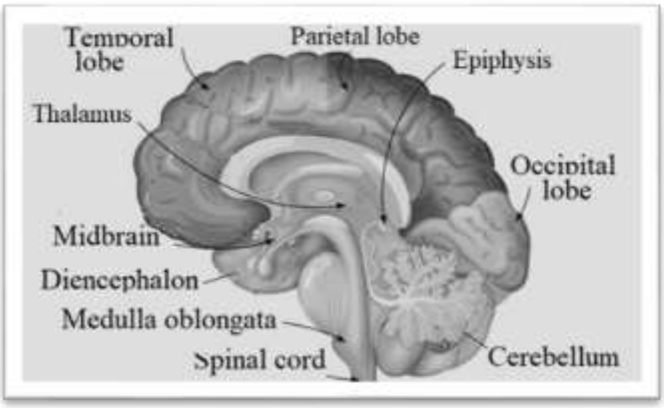

Figure 5 – Brain structure

Figure 6 – Map of the human body

The peripheral nervous system is the link between the central nervous system and organs. The nerves that make up the peripheral nervous system are not independent structures, they are formed by the processes of motor neurons, the bodies of which are located in the brain and spinal cord, and the processes of sensory neurons that carry information to the central nervous system. Thus, from the point of view of functions and structure, the division of the nervous system into central and peripheral is relative, the nervous system is one.

2.3. Functional organization of the brain

In the works of physiologists P.K. Anokhin, A.R. Luria, E.N. Sokolova, and others, different functional systems and subsystems are distinguished from the standpoint of the systemic organization of the functions of brain activity. The classic version of the integrative activity of the brain is represented as the interaction of three main functional blocks (see Fig. 7): a block for receiving and processing sensory information – sensory system (analyzers); a block of modulation and activation of the nervous system – modulating system (limbic-reticular systems) of the brain; a block of programming, launching and control of behavioral acts – motor system (motor analyzer) [14].

Neurons form two characteristic types of connections: convergent when a large number of neurons of one level are in contact with a smaller number of neurons of the next level; and divergent, in which contacts are established with an increasing number of cells of subsequent layers of the hierarchy (Fig. 7).

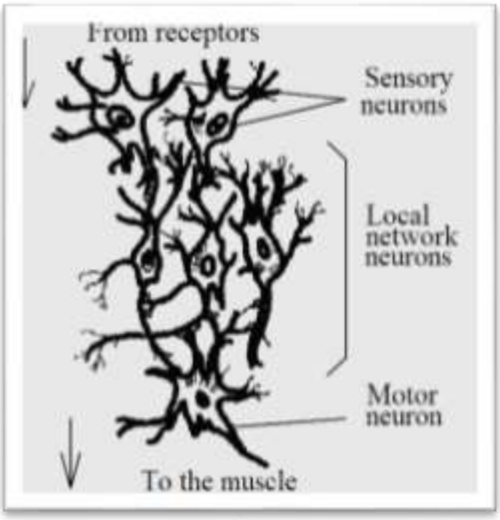

Figure 7 – Neurons of functional blocks

The signal of an external stimulus is perceived by sensory neurons that form the first (lower) level of the hierarchy. Sensory neurons (sensory system) transmit signals to the neurons of the local network, containing many forward and reverse connections with a combination of divergent and convergent connections. The nature of the signal converted in local networks determines the state of excitation of motor neurons. Local neurons (simulating system), figuratively speaking, "make a decision" which is expressed in the impact through motor neurons on muscle tissue cells.

Sensory systems (analyzers) of the brain

The main functions of sensory systems (SS) are the following: detection, discrimination, feature detection, pattern recognition; transmission, conversion, and coding of signals. Detection and primary discrimination of signals are provided by receptors, and detection and recognition of signals – by neurons of the cerebral cortex. Transmission, transformation, and encoding of signals are carried out by neurons of all layers of sensory systems. The sensory (afferent) system starts to act when some environmental phenomenon affects the receptor [15].

Receptors convert external influences into a neuronal signal. Fig. 8 demonstrates receptors that belong to different sensory systems but are similar both in structure and function. They all encode the external physical impact in the form of neuronal signals. Each sensory nerve may contain several parallel channels, each of which carries slightly different information. Thus, the visual tract has a color transmission channel called small-cell, and a channel for transmitting the shape and size of an object called large-cell. In the same way, somatosensory pathways combine channels for the transmission of touch, pressure, pain, and some other feelings [16].

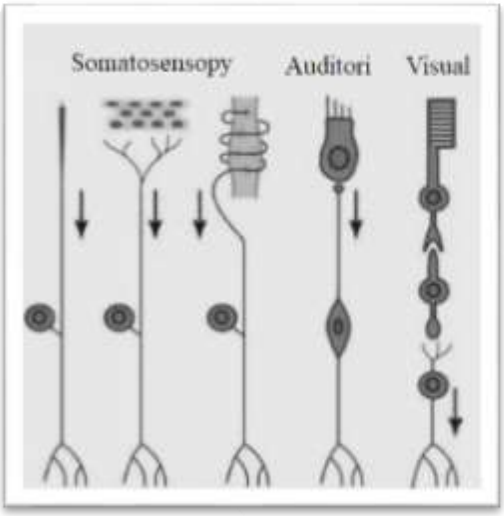

Figure 8 – Receptors of sensory systems

In each receptor, the influencing physical factor (light, sound, heat, pressure) is converted into an action potential, a nerve impulse. The frequency of impulses and the total number of receptors that transmit impulses reflect the strength of the stimulus, the size of the object, and its other characteristics.

The analyzer is a multi-level system with a hierarchical principle of organization. The base of the analyzer is the receptor surface, and the top is the projection zones of the cerebral cortex. Each level is a collection of cells whose axons go to the next level. The axons of the cells of the upper level go beyond the analyzer. Relationships between successive levels of analyzers are built on the principle of "divergence-convergence". The higher the neuronal level of the analyzer system, the greater number of neurons it includes [15].

An additional contribution to the process of acquiring individual experience is made by the modulating system which has a "non-specific" activating effect on the corresponding analyzer. The activating effect is achieved through an orienting-exploratory reflex or attention. According to Yu. Konorsky, this activation process is a necessary prerequisite for the transformation of potential cortical connections into active ones, i.e. it enables the formation of gnostic neurons, gnostic zones, and the cognitive system.

The modulating system of the brain is an apparatus that acts as a regulator of the level of wakefulness, as well as selective modulation and actualization of the priority of a particular function. The first source of activation is the internal activity of the organism or its needs. The second source of activation is associated with exposure to environmental stimuli. Limitation of contact with the external environment (sensory deprivation) leads to a significant decrease in the tone (excitability) of the cerebral cortex [14].

The motor system of the brain is the motor analyzer (in the terminology of I.P. Pavlov), or integrative-starting system that takes a special place in the functional organization of the brain. The motor areas are characterized primarily by the synthesis of excitations of various modalities with biologically significant signals and motivational influences. They are characterized by a further, final transformation of afferent influences into a qualitatively new form of activity, aimed at the fastest exit of efferent excitations to the periphery, i.e. to the apparatus for realizing the final stage of behavior. The next most important feature that distinguishes the work of this functional block from the afferent one is that the processes here go in a downward direction, starting from the highest – tertiary and secondary zones of the cortex. In the higher parts of the integrative-starting block, motor programs are formed, and then they pass to the apparatus of lower motor formations (primary cortical zones; stem and spinal motor nuclei) [15].

2.4. Reflex activity of the nervous system

The discovery by the famous Russian physiologist and Nobel Prize winner I.P. Pavlov of the main mechanism of higher nervous activity – the conditioned reflex – became one of the revolutionary achievements in natural science. With the knowledge of the dynamics of education and changes in conditioned reflexes, the discovery of the complex mechanisms of the activity of the human brain and the identification of patterns of nervous activity began.

I.P. Pavlov experimentally investigated the features of the functioning of reflexes and used the conditioned reflex as a method for studying nervous activity. The physiologist associated the principle of the synthesis of external influences and internal states with the concept of a conditioned reflex.

Innate forms of behavior

Animal behavior is primarily aimed at individual and species self-preservation. In the process of phylogenesis, a number of innate reflexes have been formed, each of which performs its specific functions and takes part in maintaining the normal functioning of the body. I.P. Pavlov called such innate reactions unconditioned reflexes. The unconditioned reflex represents a specialized integration – a connection between certain afferent systems and a complex efferent act. Stimuli that cause a specific reflex reaction are called unconditioned stimuli.

Unconditioned reflexes are reflexes that do not require special conditions for their occurrence. They are genetically predetermined, rigidly "tailored" to certain environmental conditions corresponding to a given species, and are characterized by a stereotyped, species-specific sequence of behavioral act implementation. They arise when an adequate stimulus for each of them appears and ensure the performance of the most vital functions, regardless of changing environmental conditions. Reflexes are innate mechanisms. They are formed in the process of development; some of them subsequently disappear, for example, the infantile grasping reflex. The unconditioned reflex is shown in Fig. 3. A sensitive neuron perceives receptor irritation, converts them into nerve impulses, and transmits them to interneuron 1 and interneuron 2 in the CNS. Interneuron 1 processes information and transmits control nerve impulses to the executive neuron that generates control signals for the executive body. Interneuron 2 allows or forbids the execution of commands by Interneuron 1.

A conditioned reflex is an early adaptive reaction that is individually formed by the conditions of life and carried out by the higher parts of the central nervous system. The biological meaning of the conditioned reflex is to translate neutral external stimuli into meaningful signals that adjust the body's behavior to a specific situation. For the emergence of a conditioned reflex, multiple coincidences in time of the conditioned and unconditioned stimulus are necessary, and the conditioned stimulus must precede the unconditioned one. The first stage in the formation of any conditioned reflex is reduced to an unconditioned orienting reflex.

The orienting reflex is a reflex to novelty that occurs in response to any fairly rapidly occurring change in the environment and refers to the unconditioned reflexes. The orienting reflex is aimed at the sensory selection of a new object and at assessing the significance of the stimulus. The orienting reflex develops over time in two phases:

1. The initial phase is characterized by the cessation of current activity and fixation of the posture. This phase is based on general inhibition.

2. Phase of stimulus analysis, determination of its novelty and significance.

The biological meaning of the conditioned reflex lies in the fact that numerous external stimuli surrounding the animal in natural conditions and in themselves not of vital importance, preceded in the experience of the animal by food or danger, the satisfaction of other biological needs, begin to act as signals by which the animal guides his behavior.

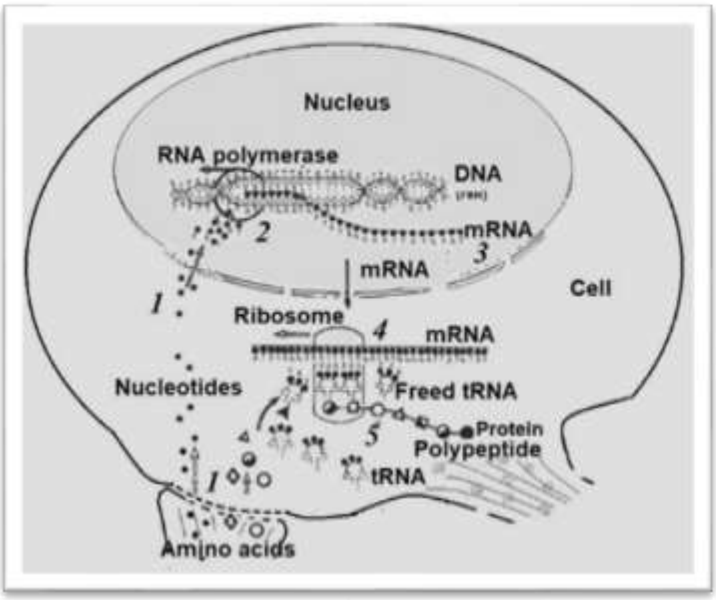

Figure 9 – Scheme of protein synthesis in the ribosome

Imitation (imitative) behavior

Stimulus-dependent learning includes imitation (imitative) behavior. As a result of imitation, an animal or person performs typical actions, learning by direct observation of the behavior of adults of its species. Thus, the conditioned reflexes are signals in nature, they allow you to change your behavior in connection with a specific situation [10].

The mechanism of the realization of reflexes

Information about instincts and unconditioned reflexes is encoded in the deoxyribonucleic acid (DNA) molecule. Decoding is carried out with the help of ribosomes that consist of the large (5) and the small (4) subunits (see Fig. 9). The information stored in DNA is encoded in a special way. The DNA code is made up of four "characters", or nucleotides. In DNA strands, nucleotides are connected one after another in long chains.

Nucleotides (external information) enter the cell nucleus (1) (Fig. 9). A special enzyme – RNA polymerase – binds to a DNA (2) a molecule and creates a "mirror copy" – informational ribonucleic acid (mRNA) (3). The small subunit reads information from the informational RNA

(4). A special transfer RNA molecule (tRNA) supplies amino acids for synthesis. The large subunit attaches an amino acid to the synthesized protein chain (5). The transfer RNA carrying the corresponding amino acid approaches the active codon and associates with it. A peptide bond of a new amino acid is formed with the protein under construction [2].

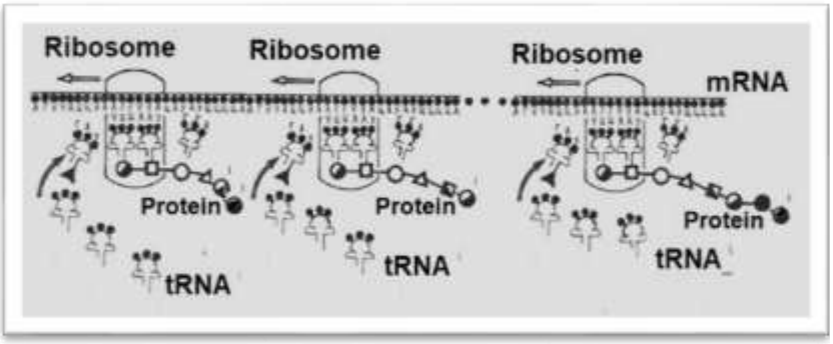

Figure 10 – Synthesis of proteins in the polysome

Protein is synthesized. In cells, the composition of the ribosome can change, and these changes depend on the state of the external environment.

Protein biosynthesis in a cell does not take place on one ribosome (Fig. 10). As a result, a complex of ribosomes (polysome) is formed, which simultaneously and independently of each other participate in the synthesis of protein molecules using the same mRNA. Thus, the information contained in mRNA is simultaneously translated by many ribosomes, and several protein molecules are synthesized in the cell. Ribosomes synthesize protein from amino acids based on the genetic information of DNA.

Ribosomes are present in all cell types. But in ordinary cells, ribosomes are busy deciphering genetic information and synthesizing proteins, which are building materials for various organs. In the nerve cell, information is processed and protein synthesis contributes to the implementation of unconditioned reflexes and the formation of conditioned reflexes, therefore, coding and memorization of new information. Those proteins, each of which has its own specific form, serve as a means of coding signs of information, and a packet of impulses accompanying the transfer of information from neuron to neuron characterizes the strength of the sign and its occurrence in time.

Acquired behaviors

Acquired involuntary processes are not reflexes. They are complex processes called automated skills and depend on practice.

Characteristic features of intelligence are the ability to perceive skills, knowledge, learning, generalization, accumulation of experience, and adaptation to changing conditions. Thanks to these functions, the brain can solve a variety of tasks, as well as easily reorganize from solving one problem to another. Thus, the brain endowed with intelligence is a universal tool for solving a wide range of problems, especially non-formalized ones, for which there are no standard, previously known methods of solving. The human brain has such qualities as the distributed representation of information and massive parallelism of its processing, error tolerance, and low power consumption. These qualities are absent in modern computer systems.

There are many criticisms that the biological brain or biological neural networks work in a completely different way from the popular now computer neural networks. Such comments are resorted to by various specialists (biologists, neurophysiologists, and specialists in computer science and machine learning), but there are very few concrete proposals to correct this situation.

As a part of the Human Brain Project, a model of a small fragment of the mouse cerebral cortex was created, and its creators took into account a lot. 3D models of neurons were recreated from real neurons, one of the variants of the Hodgkin-Huxley models was used, various types of neurons and neurotransmitters were taken into account, and there is no doubt that the model really corresponds to the biological analog. A lot of resources and time were spent on this, but it did not give significant results due to the fact that it was impossible to see significant processes in such a small size due to the paradox of neuron efficiency. Therefore, the way of detailed repetition of biology is extremely time-consuming. The key to success is the ability to understand how neural tissue and neurons work on a larger scale.

2.5. Basic requirements for an artificial neural network for the development of highly intelligent systems

1. Artificial neural networks (considered here as a brain of an intelligent system), as well as natural biological neural networks (brain of biological systems) should be formed on an artificial neuron, which is as much similar to a biological neuron as possible. Such artificial neuron (neuro-like element) is proposed and described in the first part of the paper [2].
2. An ANN must consist of the following functional blocks:
   1) a block for receiving and processing sensory information – sensory system;
   2) a block of modulation and activation of the nervous system – modulating system;
   3) a block of programming, launching, and control of behavioral acts – motor system (motor analyzer).
3. The system should have a mechanism for the formation of unconditioned and conditioned reflexes.
4. It must possess the set of unconditioned reflexes that allow the system to ensure its life cycle of development and existence in the environment.
5. It must perceive internal information from the controlling and executive subsystems.
6. It must perceive and process external information simultaneously in the subsystems of vision, hearing, touch, etc.
7. It must memorize the perceived information.

3. Neural-like growing networks

The main functional unit of the structure of the “nervous system” of intelligent systems is an artificial neuron (neural-like element).

A neural-like element consists of a device (analogous to the cell body) with many excitatory and inhibitory $\vec{a}, \vec{a}'$, modulating $\vec{b}$ inputs (analogous to dendrites), and one output $\boldsymbol{Q}$. The output (analogous to an axon) consists of many conductors and endings. Information (codes, bursts) is received at the inputs of the device. The device processes information and forms a neural-like growing network. In a neural-like element, analysis, distinguishing differences, classification, synthesis, generalization, and memorization of the perceived information are carried out, codes are generated for the formation of connections between neural-like elements, and, in accordance with the values of the features that characterize the input information and the level of excitation of the neural-like element is determined [2]. All information-free neural-like elements are neural-like elements of novelty. All neuro-like elements that carry (remember) some information in themselves are neuro-like elements of identity. In the absence of information on the receptors of neural-like elements of novelty, they are in the mode of weak random background excitation. Background excitation is a constantly changing random value of excitation of a neural-like element.

Temporary memory is neural-like elements of novelty that are excited during the time of memorizing new information. When new information (information that is unknown to the system) arrives at the sensory receptors of the neural-like element, connections are formed between the nearest neural-like element of novelty (the level of excitation of which is low but higher than all other nearby neuro-like elements of novelty) and the receptors of the sensory area; the connections are assigned weight coefficients and the neural-like element – some excitation threshold. With the repeated repetition of this information, the excitation threshold increases. When the maximum excitation is reached, the neural-like element becomes the neural-like element of identity and is transferred to long-term memory.

Long-term memory is all neuro-like elements of identity.

A neural-like growing network (n-GN) is a set of interconnected neural-like elements designed to receive, analyze, and transform information in the process of interaction with objects in the real world, similar to a biological nervous system. Moreover, the number of connections included in the neural-like element is equal to the number of features characterizing the input information (for example, color, size, shape, etc.), and each connection coming to the neural-like element is assigned a weight coefficient characterizing the significance of this feature (for example, brightness). Each neural-like element is assigned a certain excitation threshold. In the process of receiving and processing information, the network changes its structure.

N-GN is described as a directed graph where neural-like elements are represented by its vertices and connections between elements – by its edges. Thus, the network is a parallelized dynamic system with a directed graph topology that performs information processing by changing its state and structure in response to environmental influences. In the theory of multiconnected neural-like growing networks, the main concepts are the concepts of structure and architecture which reveal the scheme of connections and interactions between the network elements: topological (spatial) structure is a directed graph of connections of network elements; the logical structure defines the principles and rules for the formation of links and elements of the network, as well as the logic of its functioning. The network architecture is determined by the connection scheme of the physical elements of the network and the rules for the formation of links and elements, as well as the logic of its functioning.

Neural-like growing networks are a new type of neural networks that include the following classes: multiply connected (receptor) neural-like growing networks (mn-GN); multiconnected (receptor) multidimensional neural-like growing networks (MMN-GN); multiply connected receptor-effector neural-like growing networks (mren-RS); multiply connected multidimensional receptor-effector neural-like growing networks (mren-GN) [17–21].

3.1. A multiply connected (receptor) neural-like growing network

A multiply connected (receptor) neural-like growing network is an acyclic graph in which the number of arcs entering the vertices of the graph a_i is equal to the number of features n characterizing the input information, and each arc d_i arriving at the vertex a_i corresponds to a certain weight coefficient m_i characterizing the significance of this feature. Each vertex a_i is assigned a certain excitation threshold. The vertices that do not have incoming arcs are called receptors, and the remaining vertices are called neural-like elements.

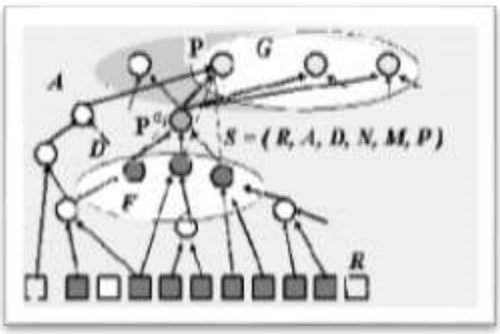

Figure 11 – Topological structure of mn-GN

The topological structure of the mn-GN is represented by a connected directed graph (Fig. 11). With the help of graphs in the theory of mn-GN, the processes of passing and storing information in the network are considered. Neural-like growing networks are formally defined as follows:

$$\boldsymbol{S = (R, A, D, M, P, N)},$$

where $\boldsymbol{R}\{r_i\},\ i=\overline{1,n}$ is a finite set of receptors; $\boldsymbol{A}=\{a_i\},\ i=\overline{1,k}$ is a finite set of neural-like elements; $\boldsymbol{D}=\{d_i\},\ i=\overline{1,e}$ is a finite set of arcs connecting receptors with neural-like elements and neural-like elements among themselves; $\boldsymbol{P}=\{p_i\},\ i=\overline{1,e}$ where P is the excitation threshold of the vertex a_i, $P=f(m_i)>P_0$ (P_o is the minimum allowable excitation threshold), provided that the set of arcs $\boldsymbol{D}$ coming to the vertex a_i, corresponds to the set of weighted coefficients $\boldsymbol{M}=\{m_i\},\ i=\overline{1,w}$, and m_i can take both positive and negative values.

The logical structure of the mn-GN is determined by a set of rules for its construction and functioning. These rules are the following.

Rule 1. If during the perception of information a subset of vertices $\boldsymbol{F}$ is excited from the set of vertices that have a direct connection with the vertex a_i and $\overline{\overline{F}}\geq h$, then the connections of the vertex a_i with the vertices from the subset $\boldsymbol{F}$ are eliminated and a new vertex a_{i+1} joins the network, the inputs of which are connected to the inputs of all vertices of the subset $\boldsymbol{F}$, the output of the vertex a_{i+1} is connected to one of the inputs of the vertex a_i, and the incoming connections of the vertex a_{i+1} are assigned weight coefficients m_g corresponding to the weight coefficients of the liquidated connections of the vertex a_i, and the vertex a_{i+1} is assigned the excitation threshold P_i equal to the sum of the weight coefficients of the links included in the vertex a_{i+1}, or the excitation threshold P_i equal to $f(m_i)$ is assigned (to some function of the weight coefficients of the links included in the vertex a_{i+1}). The outgoing connection of the vertex a_{i+1} is assigned the weight coefficient m_{i+1}. Connections originating from receptors are assigned a weight coefficient m_{ri} (Fig. 12).

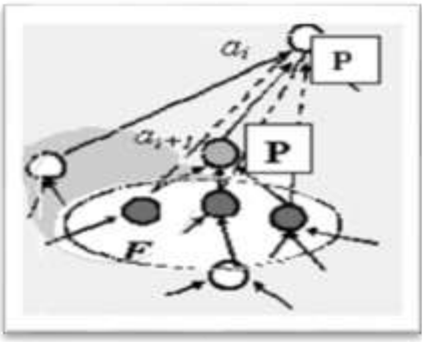

Figure 12 – Rule 1

Rule 2. If a subset of vertices $\boldsymbol{G}$ and $\overline{\overline{G}}\geq h$ is excited during the perception of information, then a new associative vertex a_{i+1} joins the network which is connected by incoming arcs to all vertices of the subset $\boldsymbol{G}$. Each of the outgoing arcs is assigned a weight coefficient mi, and the new vertex a_{i+1} is assigned an excitation threshold P_{ai+1}, equal to the sum of the weight coefficients mi of the incoming arcs or an excitation threshold P_i equal to $f(m_i)$ (some function of the weight coefficients of the links included in the vertex a_{i+1}) is assigned. The new vertex a_{i+1} is excited (Fig. 13).

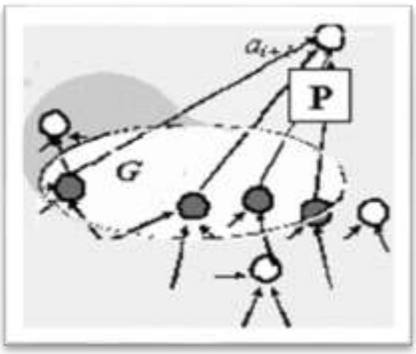

Figure 13 – Rule 2

The perception of information by a person is the result of the impact of an object, object, or situation on the receptors of the organs of vision, hearing, smell, taste, and touch. At the same time, the past experience of a person and previously acquired knowledge are actively involved. Turning to them, one can attribute the information received to already known phenomena or separate it from the general mass into a separate category.

Thus, in biological environments, information about the same object or class of objects is presented in different displays in visual, sound, verbal, tactile, etc. In this regard, when modeling descriptions of the outside world, it is necessary to be able to reflect these descriptions in various interconnected spaces. Such a structure is multiply connected multi-dimensional neural-like growing networks that describe objects or classes of objects in various information spaces.

An information space is an area of a neural-like growing network, consisting of a set of vertices and arcs, combined into a single information structure of one of the mappings.

Multiconnected multidimensional neural-like growing networks (mmn-GN) is a set of interconnected acyclic graphs that describe neural-like growing networks in various information spaces. Formally, mmn-GN is given by five values:

$$S = (R, A, D, P, N),$$

when $R \supset R_l, R_r, R_v;\ A \supset A_l, A_r, A_v;\ D \supset D_l, D_r, D_v;\ P \supset P_l, P_r, P_v$, where R_l, R_r, R_v are a final subset of receptors; A_l, A_r, A_v are a finite subset of neural-like elements; D_l, D_r, D_v are a finite subset of arcs; P_l, P_r, P_v are a finite subset of the excitation thresholds of neural-like elements belonging, for example, to the linguistic, speech, or visual information space; and N is a finite set of variable connection coefficients. The topological structure of mmn-RS is shown in Fig. 14.

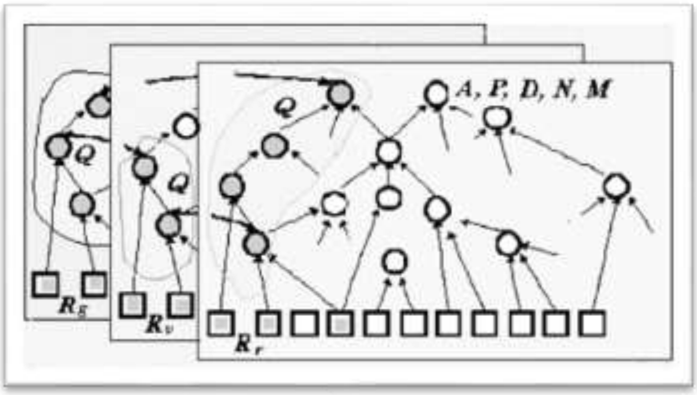

Figure 14 – Combining descriptions of objects or situations in various information spaces mmn-GN

Rule 3. If when perceiving information presented in different information spaces, a subset Q of end vertices is excited, then these vertices are connected to each other by bidirectional arcs.

In a multidimensional neural-like growing network, the logical structure for each information space $A_l, A_r, ..., A_v$ is determined by rules 1, 2, and 3. According to rule 3, descriptions of objects or situations in different information spaces are combined. At the same time, a subset Q of the end vertices of the described object, conditions, or situations is allocated in mmn-GN (Fig. 14).

3.2. Multiconnected receptor-effector neural-like growing networks

The basic principle of the physiology of higher nervous activity is known to be the basic law of biology – the unity of an organism and the environment. This law provides for the adaptive variability of the organism relative to the environment. The adaptive behavior of any organism is based on the ability to learn, i.e. the ability to remember the consequences of one's actions. We can say that the study of intelligent behavior is, to some extent, the study of the ability to acquire knowledge about the connections in the surrounding world. There is some formal difference between learning and memorization. In learning, emphasis is placed on the acquisition of knowledge, and in memorization – on the storage and usage of existing knowledge in the form of specific information. "The organism learns by building sensory-motor schemes: it extracts from its experience the relationship between the information perceived by its sensory systems and its actions (motor activity)" [22].

The interaction of biological objects with the environment is carried out through acts of movement. We perform various movements – walking, gestures, facial expressions, writing, speech, etc. It is generally accepted that the regulation of the behavior of biological systems, including the regulation of movements, is based on two principles: the principle of sensory corrections of the current movement and the principle of direct control.

In order to provide the possibility of modeling the processes of learning and acquiring knowledge, regulating the movement and behavior of mobile robots, multiply connected receptor-effector neural-like growing networks have been developed.

In multiply connected receptor-effector neural-like growing networks, receptor $\boldsymbol{R}$ fields (an analog of the sensory and receptor regions of biological objects), effector $\boldsymbol{E}$ fields (an analog of the motor region of biological objects), receptor $\boldsymbol{A}_r$ and effector $\boldsymbol{A}_e$ zones are distinguished. Receptor-effector neural-like growing networks are subdivided into single-layer, multilayer, and multi-dimensional receptor-effector neural-like growing networks.

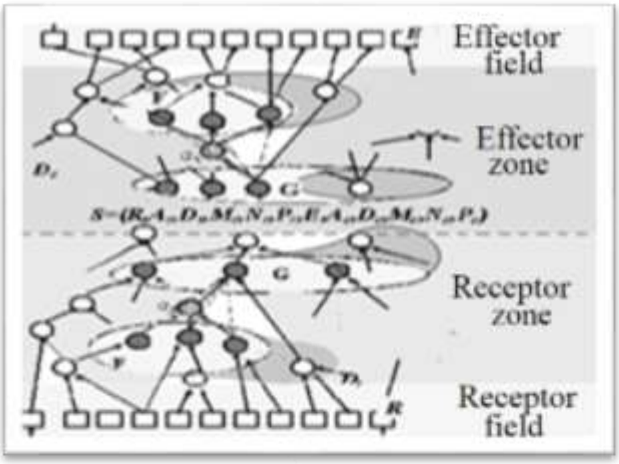

Figure 15 – Topological structure of mren-GN

A two-sided acyclic graph consisting of receptor and effector zones, in which each arc of the receptor zone arriving at the vertices of this zone corresponds to a certain weight coefficient, and the vertices to a certain excitation threshold, and each arc of the effector zone arriving at the vertices of this zone corresponds to a certain weight coefficient, and the vertices are a certain threshold of excitation called a multiconnected receptor-effector neural-like growing network.

The topological structure of a multiconnected receptor-effector neural-like growing network (mren-GN) is represented by a graph (Fig. 15).

In ren-RS, subsets of excited $\boldsymbol{F}_r$ and $\boldsymbol{F}_e$ vertices of the receptor and effector zones, respectively, and subsets of excited vertices of the $\boldsymbol{G}_r$ and $\boldsymbol{G}_e$ network of the receptor and effector zones are distinguished. The symbols denote the cardinalities of the subsets $\boldsymbol{F}_r$, $\boldsymbol{F}_e$ and $\boldsymbol{G}_r$, $\boldsymbol{G}_e$ respectively.

Multiconnected receptor-effector neural-like growing networks are formally defined as follows:

$$\boldsymbol{S = (R, A_r, D_r, P_r, N_r, E, A_e, D_e, P_e, M_e, N_e)},$$

where $\boldsymbol{R} = \{r_i\}$, $i = \overline{1,n}$ is a finite set of receptors, $\boldsymbol{A}_r = \{a_i\}$, $i = \overline{1,k}$ is a finite set of neural-like elements of the receptor zone, $\boldsymbol{D}_r = \{d_i\}$, $i = \overline{1,e}$ is a finite set of arcs of the receptor zone, $\boldsymbol{E} = \{e_i\}$, $i = \overline{1,e}$ is a finite set of effectors, $\boldsymbol{A}_e = \{a_i\}$, $i = \overline{1,k}$ is a finite set of neural-like elements of the effector zone, $\boldsymbol{D}_e = \{d_i\}$, $i = \overline{1,e}$ is a finite set of arcs of the effector zone, $\boldsymbol{P}_r = \{P_i\}, \boldsymbol{P}_e = \{P_i\}$, $i = \overline{1,k}$, where P_i is the excitation threshold of the top $a_{ir}, P_i = f(m_i)$ provided that the set of arcs $\boldsymbol{D}_r$ and $\boldsymbol{D}_e$, coming to the vertex a_{ir}, a_{ie}, corresponds to the set of weight coefficients $\boldsymbol{M}_r = \{m_i\}$, $\boldsymbol{M}_e = \{m_i\}$, $i = \overline{1,w}$, and m_i can take both positive and negative values. $\boldsymbol{N}_r$ and $\boldsymbol{N}_e$ are variable coefficients of connectivity of the receptor and effector zones.

Logical structure of mren-GN

Since mren-RS includes receptor and effector zones that interact with each other, it becomes necessary to develop rules for the construction and functioning of the network. These rules are formulated as follows.

Rule 4. If when information is perceived by the receptor field, a subset $\boldsymbol{F}_r$ is excited from the set of vertices that have a direct connection with the vertex air, while $\overline{\overline{F}} \geq h$, and when the effector zone generates actions, the subset $\boldsymbol{G}_e$ and $\overline{\overline{G}} \geq h$ are excited, then the connections of the vertex with the vertices from the subset $\boldsymbol{F}_r$ are eliminated and a new vertex a_{i+1}^r joins the network, the inputs of which are connected to the outputs of all vertices of the subset $\boldsymbol{F}_r$, and the output of the vertex a_{i+1}^r is connected to one of the inputs of the vertex a_i^r, and the incoming links of the vertex a_{i+1}^r are assigned weight coefficients mi corresponding to the weight coefficients of connections of the a_i^r vertex, and the a_{i+1}^r vertex is assigned the excitation threshold Pa_{i+1} which is equal to the function of the weight coefficients of the connections included in the a_{i+1}^r vertex. The outgoing connection of the vertex a_{i+1}^r is assigned a weight coefficient mi equal to $f(Pa_{i+1}^r)$. The bonds originating from the receptors are assigned a weight coefficient equal to the feature code b_i corresponding to the given receptor. In the effector zone, a new associative vertex a_{i+1}^e joins the network which is connected by outgoing arcs to all vertices of the $\boldsymbol{G}_e$ subset. Each of the outgoing arcs is assigned a weight coefficient m_i equal to $f(Pa_i^e)$ of the corresponding vertex from the subset $\boldsymbol{G}_e$, and the new vertex a_{i+1}^e is assigned the minimum excitation threshold Pa_{i+1}^e which is equal to the function of the weight coefficients m_i of the incoming arcs. The top of the a_i^r receptor zone is connected by an outgoing arc to the new top of the effector zone. After the introduction into the network, new vertices immediately become excited (Fig. 16).

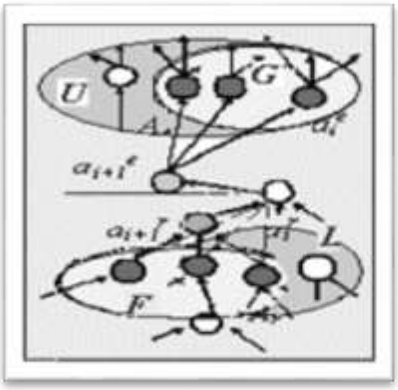

Figure 16 – Rule 4

Rule 5. If during the perception of information by the receptor field a subset $\boldsymbol{F}_r$ is excited from the set of vertices that have a direct connection with the vertex air of the receptor zone, while $\overline{\overline{F}} \geq h$, and the generation of actions is made by the effector zone, a subset $\boldsymbol{F}_e$ is excited from the set of vertices that have a direct connection with the vertex a_i^e of the effector zone and $\overline{\overline{F}} \geq h$, then the connections of the vertex air with the vertices from the subset are eliminated and a new vertex a_{i+1}^r joins the network, the inputs of which are connected to the outputs of all vertices of the subset $\boldsymbol{F}_r$, and the output of the vertex a_{i+1}^r is connected to one of the inputs of the vertex air, and the input the links of the vertex a_{i+1}^r are assigned the weight coefficients mi corresponding to the weight coefficients of the liquidated

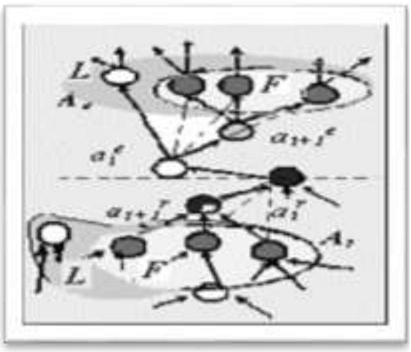

Figure 17 – Rule 5

links of the vertex air, and the vertex a^r_{i+1} is assigned the excitation threshold Pa^r_{i+1} which is equal to the function of the weight coefficients of the links included in the vertex. The outgoing connection of the vertex a^r_{i+1} is assigned a weight coefficient mi equal to $f(Pa^r_{i+1})$. The bonds originating from the receptors are assigned a weight coefficient equal to the feature code bi corresponding to the given receptor. In the effector zone of connection, vertices a^e_i with vertices from the subset $\boldsymbol{F}_e$ are eliminated and a new vertex a^e_{i+1} joins the network, the outputs of which are connected to the inputs of all vertices of the subset $\boldsymbol{F}_e$, and the input of the vertex a^e_{i+1} is connected to one of the outputs of the vertex a^e_i, and the incoming connections of the vertex a^e_{i+1} are assigned the weight coefficients mi corresponding to the weight coefficients of the liquidated links of the vertex a^e_i, and the vertex a^e_{i+1} is assigned the excitation threshold Pa^e_{i+1} which is equal to the function of the weight coefficients of the outgoing links of the vertex a^e_i. The incoming connection of the vertex a^e_{i+1} is assigned a weight coefficient mi equal to $f(Pa^e_i)$. The new apex a^r_{i+1} of the receptor zone is connected by an outgoing arc to the new apex a^e_{i+1} of the effector zone. After the introduction into the network, new vertices immediately become excited (Fig. 17).

Rule 6. If during the perception of information by the receptor field the subset $\boldsymbol{G}_r$ is excited, with $\overline{\overline{F}} \geq h$ and the generation of actions made by the effector zone, the subset $\boldsymbol{G}_e$ and $\overline{\overline{F}} \geq h$ are excited, then in the receptor zone a new associative vertex a^r_{i+1} joins the network which is connected by incoming arcs with all vertices of the subset $\boldsymbol{G}_r$. Each of the incoming arcs is assigned a weight coefficient mi equal to $f(Pa^r_i)$ of the corresponding vertex from the subset $\boldsymbol{G}_r$, and the new vertex a^r_{i+1} is assigned the minimum excitation threshold Pa_{i+1} which is equal to the function of the sum of the weight coefficients mi of the incoming arcs. In the effector zone, a new associative vertex a^e_{i+1} joins the network which is connected by outgoing arcs to all vertices of the $\boldsymbol{G}_e$ subset. Each of the outgoing arcs is assigned a weight coefficient mi equal to $f(Pa^e_i)$ of the corresponding vertex from the subset $\boldsymbol{G}_e$, and the new vertex is assigned the minimum excitation threshold Pa^e_{i+1} which is equal to the function of the weight coefficients mi of the outgoing arcs. The new apex of the receptor zone is connected by an outgoing arc to the new apex of the effector zone. After the introduction into the network, new vertices immediately become excited (Fig. 18).

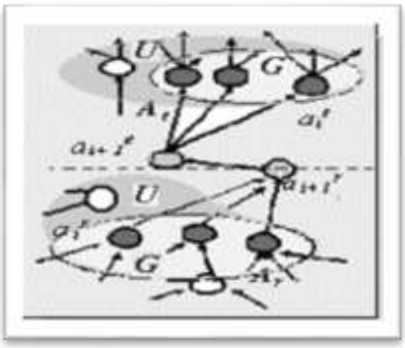

Figure 18 – Rule 6

Rule 7. If when information is perceived by the receptor field, a subset $\boldsymbol{G}_r$ and $\overline{\overline{F}} \geq h$ is excited, and a subset of $\boldsymbol{F}_e$ is excited by the effector zone from the set of vertices that have a direct connection with the vertex a^e_i of the effector zone, and $\overline{\overline{F}} \geq h$, then a new associative network is added to the network in the receptor zone the vertex a^r_{i+1} which is connected by incoming arcs to all vertices of the subset $\boldsymbol{G}_r$. Each of the incoming arcs is assigned a weight coefficient mi equal to $f(Pa_i^r)$ of the corresponding vertex from the subset $\boldsymbol{G}_r$, and the new vertex a_{i+1}^r is assigned the minimum excitation threshold Pa_{i+1}^r which is equal to the function of the weight coefficients mi of the incoming arcs. In the effector zone of connection, vertices a_i^e with vertices from the subset $\boldsymbol{F}_e$ are eliminated and a new vertex a_{i+1}^e joins the network, the outputs of which are connected to the inputs of all vertices of the subset $\boldsymbol{F}_e$, and the input of the vertex a_{i+1}^e is connected to one of the outputs of the vertex a_i^e, and the outgoing connections of the vertex a_{i+1}^e are assigned the weight coefficients mi corresponding to the weight coefficients of the eliminated links, and the vertex a_{i+1}^e is assigned the excitation threshold Pa_{i+1}^e which is equal to the function of the weight coefficients of the outgoing links of the vertex a_{i+1}^e. The incoming connection of the vertex a_{i+1}^e is assigned a weight coefficient mi equal to $f(Pa_i^e)$. The new apex of the receptor zone is connected by an outgoing arc to the apex a_i of the effector zone. After the introduction into the network, new vertices immediately become excited (Fig. 19).

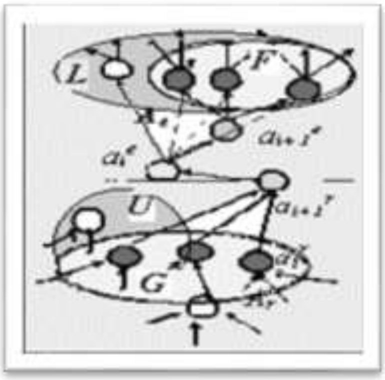

Figure 19 – Rule 7

Multiconnected receptor-effector neural-like growing networks are a dynamic structure that changes depending on external information entering the receptor field and information generated by the effector zone to the outside world. Perception, analysis, synthesis, and memorization of external information are accompanied by the introduction of new vertices and arcs into the network in the receptor zone, and the generation of action programs, behavior, and adaptation to changes in the outside world is accompanied by the introduction of new vertices and arcs into the network in the effector zone. The formation of new peaks and arcs is accompanied by the transition of some ensemble of receptors or neural-like elements, or receptors and neural-like elements of the receptor zone and an ensemble of effectors or neural-like elements, or effectors and neural-like elements of the effector zone into an excited state. The excitation process undulates through the network.

3.3. Multiconnected multidimensional receptor-effector neural-like growing networks

Multidimensional receptor-effector neural-like growing networks, using various spatial representations of information, perceive, memorize, and process descriptions of images of objects or situations in a problem area and also generate control actions on the external environment.

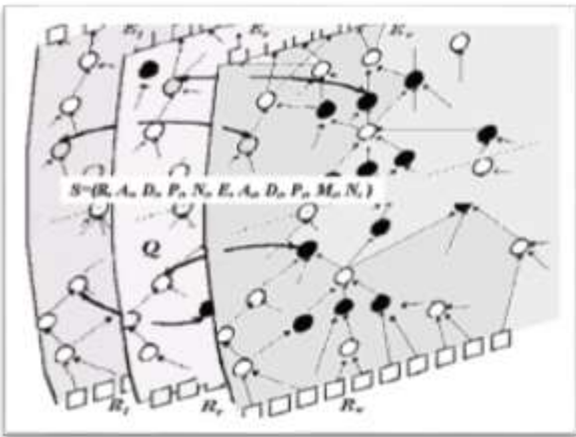

Figure 20 – Topological structure of mmren-GN

Multiconnected multidimensional receptor-effector neural-like growing networks (mmren-RS) is a set of interconnected two-way acyclic graphs that describe the state of an object and the actions it generates in various information spaces.

The topological structure of mmren-GN is represented by a graph (Fig. 20). Formally, mmren-RS are given as follows:

$$\boldsymbol{S = (R, A_r, D_r, P_r, M_r, N_r, E, A_e, D_e, P_e, M_e, N_e)}, \text{ where}$$

$$\boldsymbol{R \supset R_v, R_s, R_t;\ A_r \supset A_v, A_s, A_t;\ D_r \supset D_v, D_s, D_t;\ P_r \supset P_v, P_s, P_t;\ M_r \supset M_v, M_s, M_t;}$$
$$\boldsymbol{N_r \supset N_v, N_s, N_t;\ E \supset E_r, E_{d1}, E_{d2};\ A_e \supset A_r, A_{d1}, A_{d2};\ D_e \supset D_r, D_{d1}, D_{d2};}$$
$$\boldsymbol{P_e \supset P_r, P_{d1}, P_{d2};\ M_e \supset M_r, M_{d1}, M_{d2};\ N_e \supset N_r, N_{d1}, N_{d2};}$$

and where $\boldsymbol{R_v, R_s, R_t}$, is a finite subset of receptors, $\boldsymbol{A_v, A_s, A_t}$ is a finite subset of neural-like elements, $\boldsymbol{D_v, D_s, D_t}$ is a finite subset of arcs, $\boldsymbol{P_v, P_s, P_t}$ is a finite set of excitation thresholds of neural-like elements of the receptor zone, belonging, for example, to visual, auditory, and tactile information spaces, $\boldsymbol{N}$ is a finite set of variable connectivity coefficients of the receptor zone, $\boldsymbol{E_r, E_{d1}, E_{d2}}$ is a finite subset of effectors, $\boldsymbol{A_r, A_{d1}, A_{d2}}$ is a finite subset of neural-like elements, $\boldsymbol{D_r, D_{d1}, D_{d2}}$ is a finite subset of effector arcs zones $\boldsymbol{P_r, P_{d1}, P_{d2}}$ is a finite set of excitation thresholds of neural-like elements of the effector zone, belonging, for example, to the speech information space and action space, $\boldsymbol{N}$ is a finite set of variable connectivity coefficients of the effector zone.

The logical structure of mmren-GN is described by rules 4-7, as well as the logical structure of multiply connected receptor-effector neural-like growing networks, and additionally by rule 8, which determines the formation of links between descriptions of objects in various information spaces.

Rule 8. If when external information arrives at the receptor fields of various information spaces in the receptor zones of these information spaces, a subset $\boldsymbol{Q_r}$ of the end vertices belonging to these descriptions is excited, and at the same time, a subset $\boldsymbol{Q_e}$ of the end vertices is excited in the effector zones of the corresponding information spaces, generating a set of actions corresponding to input information, then the vertices of the receptor zones of these information spaces, which belong to the subset $\boldsymbol{Q_r}$, are connected to each other by bidirectional arcs. The vertices of the effector zones belonging to the $\boldsymbol{Q_e}$ subset are also connected to each other by bidirectional arcs (Fig. 20).

Mmren-GN is a basic structure of AI systems and a model similar to the neural networks of the human brain. Mmren-GN represents a homogeneous structure in which through modeling the basic law of biology – the unity of the organism and the environment – implemented on the basis of the unconditional-reflex activity of the nervous system and in accordance with the conditions of the external environment, knowledge, forms of behavior, and actions are acquired and accumulated.

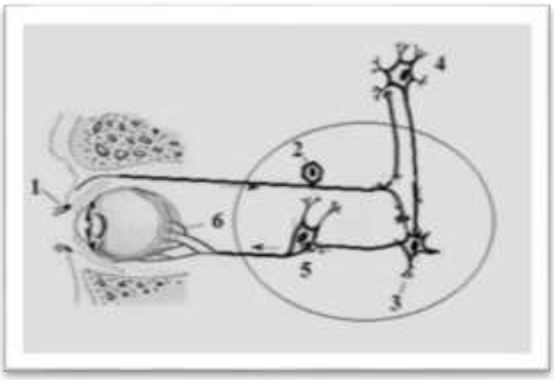

Figure 21 – Reflex arc of eyelash blinking

Modeling of the reflex arc on mmren-GN

Fig. 21 shows the reflex arc of eyelash blinking. The reflex arc includes sensitive (2), intercalary (3 and 4), and executive (5) neurons.

Irritation of receptors (1) causes a flow of nerve impulses that travel along the dendrite to the body of the sensitive neuron (2) and from it along the axon to the intercalary neuron (3) and into the medulla oblongata to the intercalary neuron (4). Information is processed by the brain, including the cortex. Then, through the intercalary neuron (3), the executive neuron (5) is excited, and the excitation along the axon reaches the circular muscles of the eye (6) and causes blinking.

Depending on the performed function, neural-like elements are divided into sensory, intercalary, and motor. Sensory neurons perceive information, transform, and transmit it to the CNS. Motor neurons generate and send commands to the working organs, ensuring the transfer of information from the central nervous system to the periphery. Intercalary neurons communicate between sensory and motor neurons and participate in information processing and command generation, ensuring the transfer of information within the CNS. Fig. 22 shows a model of a reflex arc of a robot’s eye blink, where 1 is receptors, 2 is a sensory neuron, 3 and 4 are intercalary neurons of the local network, 5 is a motor neuron, and 6 are effectors. Fig. 23 shows a model of a multidimensional imprinting reflex arc on mmren-GN. A chicken, seeing another chicken for the first time, follows it everywhere. Imprinting is also observed in other animals. Having seen the parent, the cub remembers its appearance, voice, and smell for life.

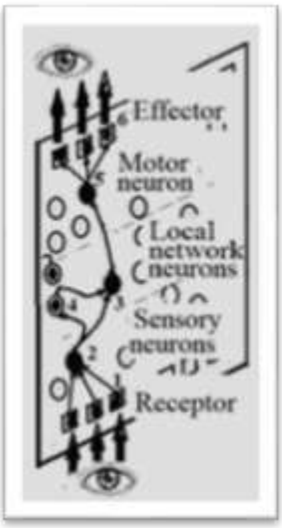

Figure 22 – One-dimensional robot eye blink reflex arc

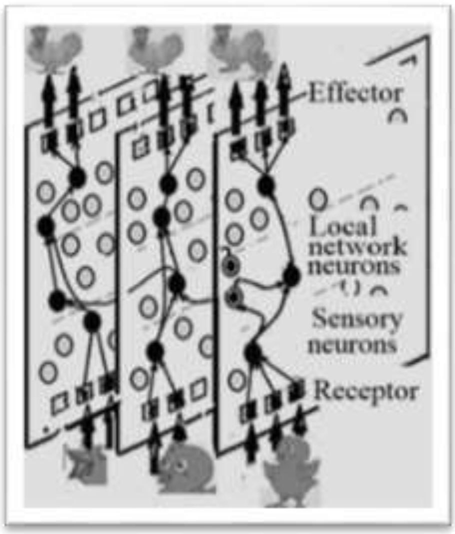

Figure 23 – Multidimensional imprinting reflex arc

Recognition and memorization of symbolic information

In the first part of the work, the process of perception, recognition, and memorization of letters and words by neural-like elements is considered (Fig. 24). As a result of this process, a multidimensional multilayer n-RS is formed. Its multilayer structure is similar to the neocortical column of the brain. During the process of learning, information is perceived simultaneously visually, audio, and tactilely (the image is perceived by the eyes, it is pronounced, heard, and recorded). To test the functioning of mmren-GN, a model of an intelligent system was developed, in which the main functions of natural intelligence are implemented (perception, analysis, synthesis, selection, and memorization of visual and symbolic information, communication, logical conclusions, etc.).

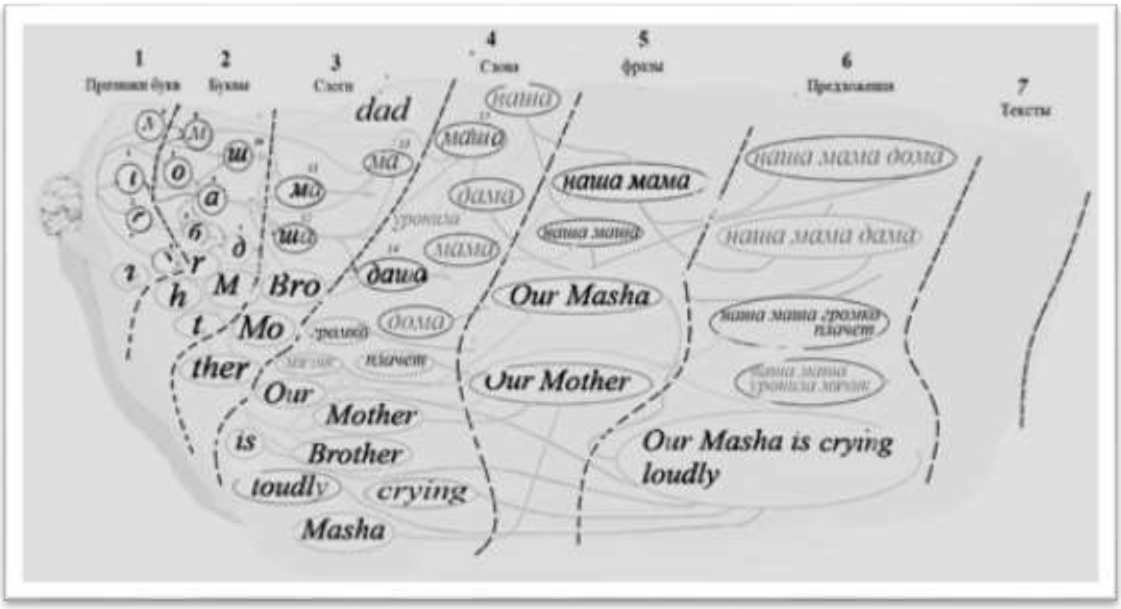

Figure 24 – Multilayer neural-like growing network

Fig. 25 demonstrates the process of face recognition from the Yale University image database “Yale FaceIMAGES_Data”. The knowledge base created on mmren-GN contains more than 900 images of faces, letters, numbers, streets, and avenues.

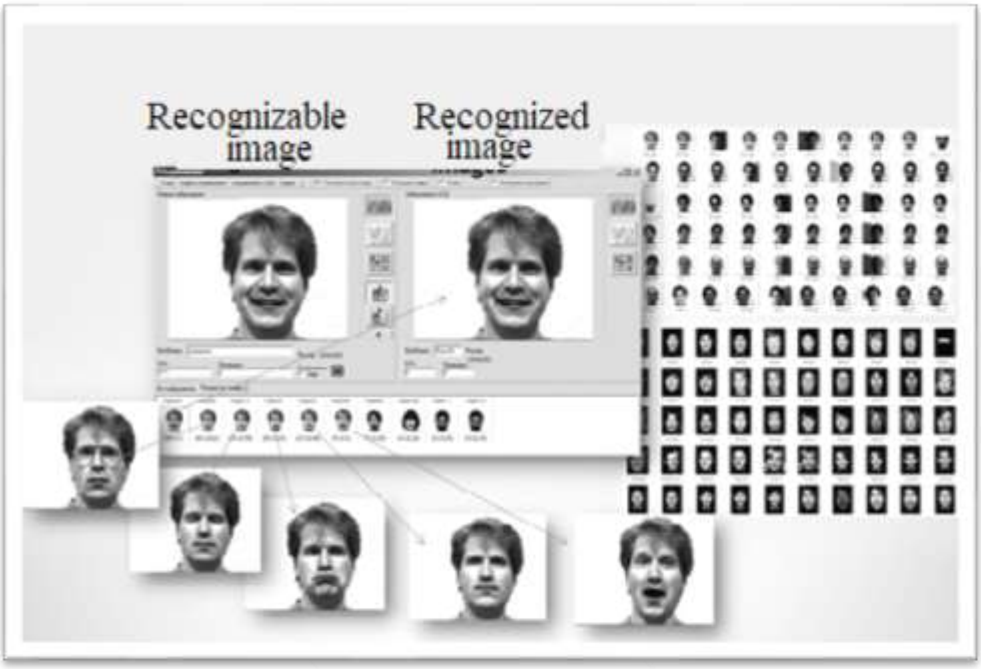

Figure 25 – Face recognition from the Yale University Image Database

The database performs the functions of perception of visual information, analysis, synthesis, recognition, and memorization of faces in real time. Replenishment of facial images is carried out in real time as information is perceived. Fig. 26 shows real-time face recognition.

Figure 26 – Real-time face recognition

4. Conclusions

Artificial neural networks, which are the basic structure of artificial intelligence systems, successfully solve many different problems. But most AI systems only achieve great solutions for narrow problems. In addition, to solve the set tasks, it is required to collect and prepare large volumes of training samples and time to complete cycles (epochs) of training. Almost all ANNs use the mathematical model of the McCollock and Pitts neuron. In this regard, training is actually reduced to multiple recalculations of the coefficients of connections between neurons. At the same time, working with large amounts of information requires the use of computers with high computing power. The artificial neuron of J. McCulloch and W. Pitts, as the main element of neural networks, is functionally very simplified in order to be an analog of a biological neuron. The presented neural-like element, the main structural unit of mmren-GN, is similar to a biological neuron. Based on consideration and analysis of the structure and functions of a biological neuron, it is concluded that huge amounts of information perceived by a person from the moment of birth and throughout his life are remembered at the molecular level in a neuron. It is shown that information processing is carried out in the neuron. Ribosomes, deciphering genetic information and synthesizing proteins, process the perceived information. Moreover, information processing is similar to information processing in a Turing machine. The structure and functions of ribosomes almost completely coincide with the structure and functions of the Turing machine. Given this fact, it can be concluded that the neuron is an analog multimachine complex – an ultra-fast molecular supercomputer with an unusually simple analog programming device.

The main requirements for artificial neural networks for the development of AGI have been developed. Multiconnected multidimensional receptor-effector neural-like growing networks are the basic structure of AGI systems and a model similar to the neural networks of the human brain. In mmren-RS, information about the outside world, its objects, their states, and situations that describe the relationship between them, as well as information about the actions caused by these states, is stored due to its reflection in the network structure, and the arrival of new information causes the formation new associative vertices and connections and their redistribution between the vertices that arose earlier while highlighting the common parts of these descriptions and actions, which are automatically generalized and classified. Mmren-RS almost fully comply with the requirements for artificial neural networks for the development of AGI.

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