Neural Network Structures: Current and Future States

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***Abstract*—Two prevailing points of view on the way of creating artificial intelligence have been presented: based on the consistent patterns the evolution of neurons of the natural nervous system went through and based on radically new patterns, different from the consistent patterns seen in the natural evolution, shall be used to develop neural network structures and programs. The main structural elements of the future artificial intelligence based on the laws of the development of human neural networks have been presented: the main types of neurotransmitters and their role in the modulation of informative signals; a principle of diffuse transmission of information through the intercellular matrix; a concept of improving efficiency of functioning neural network structures based on diffuse transmission of signals in the form of hormones, growth factors, cytokines. It was pointed out that the researchers who are aiming at the development of artificial intelligence must remember about potential negative consequences that should be taken into account and avoided at the stages of problem semantic comprehension.**

I. Introduction

Any discussions dedicated to artificial intelligence involve two prevailing points of view. As the case in point concerns the intelligence inherent in humans only, one of the points of view assumes that the approach for creating artificial intelligence shall be based on the consistent patterns the evolution of neurons of natural nervous system went through.

The other point of view is that some radically new patterns, different from the consistent patterns seen in the natural evolution, shall be used to develop neural network structures and programs. Since the organizers and the participants of the scientific conference Open Semantic Technologies for Intelligent Systems (OSTIS-2018) are basically the adherents of the latter point of view, this paper focuses on the former one.

One remark need to be made in the very beginning: the first approach assuming a certain intervention of humans in natural laws of the development of nervous system brings a potential danger. We mean here a phenomenon described in literary form by Percy Bysshe Shelly's wife Mary Shelly who wrote a novel about Frankenstein. Therefore, the researchers who are aiming at the development of artificial intelligence must remember about potential negative consequences that should be taken into account and avoided at the stages of problem semantic comprehension.

Now let us turn directly to the main structural elements of the future artificial intelligence based on the laws of the development of human neural networks.

In the neural networks of the human brain, the signals are predominantly transferred by means of electricity using the branching extensions of nerve cells. However, direct signal recognition is accomplished by means of chemical intermediaries, or neurotransmitters, allocated discretely in the form of quanta of matter, that ensure the modulation of informative signals (Figure 1). Considering a huge variety of intermediaries (neurotransmitters), ranging up to tens and hundreds of thousands, we can imagine the great variety of the modulating abilities of neural networks of the human brain. By the way, the emotional, cognitive diversity of human behavior illustrates the diversity of capabilities of the brain neural network structures demonstrated above [1-3].

The next important concept of the nervous system organization that should be considered when creating artificial intelligence, is the colossal ability of just a single neuron to process information, to store, sum and integrate various signals actually instantaneously (within fractions of milliseconds); this feature, according to a number of scientists, makes capabilities of just a single neuron (especially in the part of recognizing visual images) comparable to those of personal computer [4-6]. Human neuron network organization always includes functional diversity of individual populations of the neuron networks constituting entire neuron network structure of human brain. Specifically, neural network organization includes the groups of neurons that present acceptors of signals both from the periphery and from within the neural network. The second important neuron population mainly performs processing of incoming signals and makes decisions further transferred, in the form of electrical signals, to the neural population responsible for specific control functions in the organism. Norbert Wiener [7] and academician Pyotr Anokhin [8] deserve the credit for inventing an obligatory link in neural networks in the form of feedback, both at the level of individual populations of neural networks, and at the system level of neuron network – effector (executive subsystems) [9-10].

Functional activity of neurons is determined by efficiency

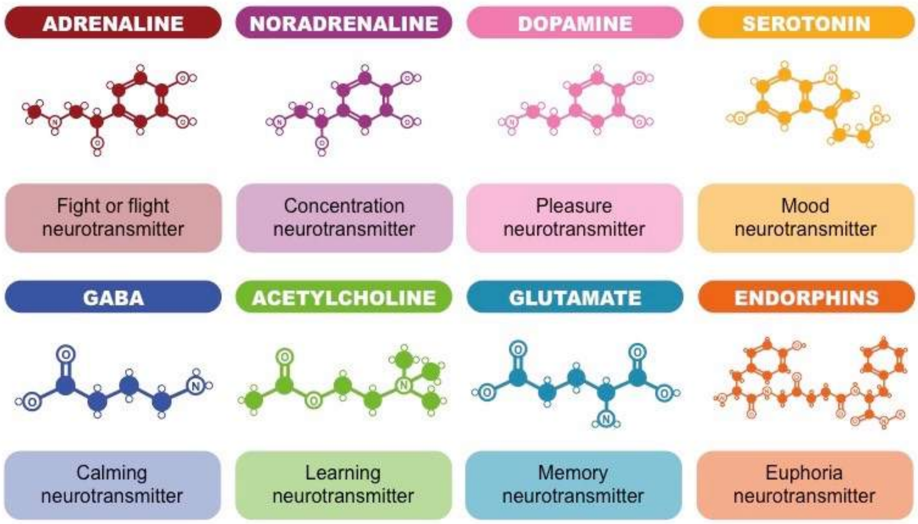

Figure 1. Chemical Structures of Neurotransmitters. Reproduced from http://www.compoundchem.com/2015/07/30/neurotransmitters/. Below is a list of the main neurotransmitters and their effect on the central nervous system of human: Adrenaline. Adrenaline is primarily a hormone released by the adrenal gland, but some neurons may secrete it as a neurotransmitter. Noradrenaline. In contrast to adrenaline, noradrenaline is predominantly a neurotransmitter that is occasionally released as a hormone. Dopamine. It is primarily responsible for feelings of pleasure, but is also involved in movement and motivation. Serotonin. Contributes to feelings of well-being and happiness. GABA. Inhibits neuron firing in the CNS – high levels improve focus whereas low levels cause anxiety. Acetylcholine. Involved in thought, learning and memory within the brain. Glutamate. Most common brain neurotransmitter. Endorphins. Release is associated with feelings of euphoria and a reduction in pain (body's natural 'pain killers').

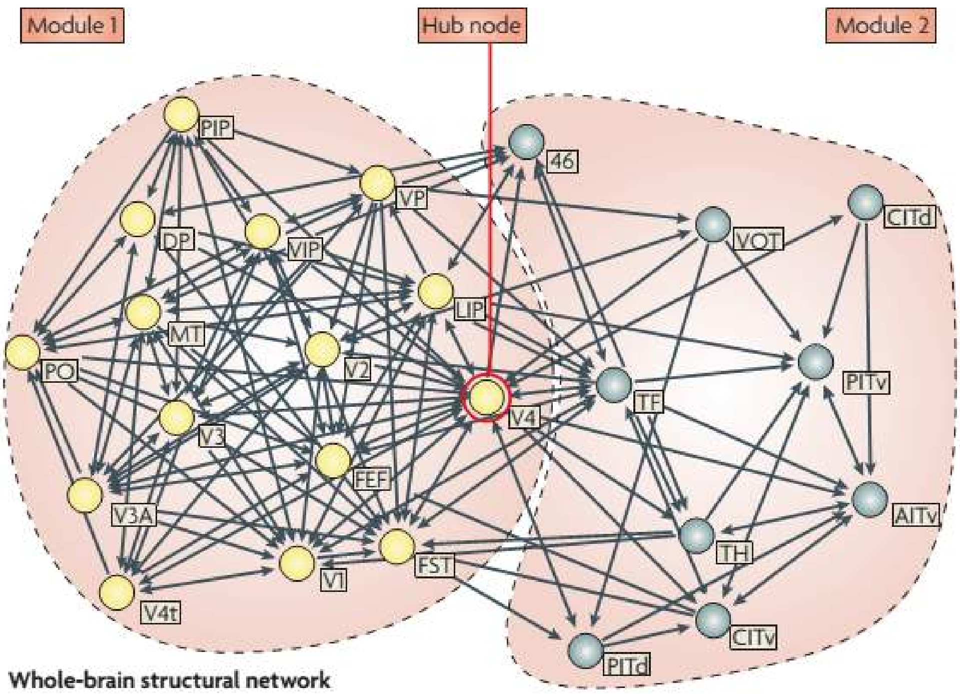

Figure 2. Whole-brain structural network constructed from histological data on the macaque cortex; each node corresponds to a brain area and the connections represent axonal projections between areas. Reproduced from [11].

of synaptic formations functioning. Plenty of signal molecules (from neurotransmitters till growth factors, amino acids and gas molecules) are involved into interneuron communications. By the way, every human has its own complex (pattern) of signal molecules which significantly determine intellectual features and personality. Unfortunately, namely the targets of signal molecules – neural networks and synapses – are the most sensitive to inflammatory factors, toxins, endogenous and synthetic neutrophilic substances exposure. Acute or chronic disruption of interneuron communications is always followed by failure in neural networks integrative work. Development of pathological processes in brain becomes the result of such failures. These processes may acquire functional character after initiation of plastic processes in nerve tissue including stem cells. On the other side, disturbance of brain plasticity leads to development of destructive transformations in neurons, synapses and glial cells. The process becomes irreversible, and patients usually visit doctor only at this stage. The standard treatment scheme is usually applied in clinical practice: medicines with neurotropic effect. Additional "intervention" in neural networks activity transforms their regular work. Pathological process becomes chronic. Then the doctor decides to change treatment scheme. But where to shift focuses in correction of neural networks functions? Special methods are applied in preclinical studies in order to assess the effects of new substances on functional state of neurons and interneuron communications. In particular, neurophysiological techniques allow quantitatively and dynamically establish the efficiency of signals transmission in nerve tissue and assess synaptic plasticity. Modern neurophysiological techniques of electrical events registration at the level of single synapse or part of neuron membrane (patch-clamp) increase opportunities in assessment of neural networks functions in health and disease. But there are difficulties in common analysis of revealed patterns at the levels of neuron membrane part and multicomponent neural network. Integrative analytic approach with computer modelling is needed. Otherwise the diversity of mechanisms of neurotropic substances action on central nervous system (from synapses and cells till integrative level of brain and spinal cord) cannot be ascertained.

Interneuron communications modelling at the level of integral brain is one of the technologies to answer the raised questions. Formation of such models became available after development of numerical methods of analysis of biophysical processes of data processing in biological neural networks. Data processing at this level requires special hardware and software design. For example, the project "Blue Brain" uses supercomputer Deep Blue (IBM) for detailed modelling of one part on cerebral cortex [12, 13]. One can imagine the required level of computer to model not the one part of cerebral cortex, but the functions of whole brain. That is why methods of computer modelling attract special attention of researchers and doctors.

In many cases models of neural networks with certain configuration are used in the analysis of experimental data. There is popular model [1] consisting of several hundred input neurons forming synaptic contacts with output neuron, which is used in numerous studies of synaptic plasticity investigation. This model considers spike-timing dependent plasticity, revealed in many brain regions [12]. Change of synaptic conductivity in the model is determined only by time parameters of pre- and postsynaptic activation [12-14]. Such relatively simple model provides insight into essential features of neural network. It is all about stability of output activity after change of different parameters and formation of competitive input signals during interaction of synapse groups. In this case, the increase in conductivity in one group of synapses is accompanied with the decrease in conductivity of other synapses.

Ideas of competitive learning appeared in theoretical studies dedicated to pattern recognition and self-management in neural networks [12, 13], as well as in modelling of the processes of topological mapping formation (correlation between receptor and the area of brain cortex) [12]. Hebb's theory of competitive learning is used in modelling of patterns formation, maps of brain cortex and selectivity columns and is characterized as "flexible, simple and useful" [12]. For example, only part of information presented at eye retina can be processed at any specific time (namely the information which is in the focus of attention). That is why populations of neurons responsible for mapping of certain patterns compete for priority of their information processing [12, 13]. The effect of medicinal substance in these models is considered as factor influencing on certain features of used model. Conditions of spike potentials generation and electrical processes at the level of pre- and postsynaptic membrane, characterizing synaptic transmission are considered the most important processes [15]. Influence of substance or other disturbing factors is manifests as change of threshold of spike potentials generation that can be easily detected experimentally and realized in model neuron. Main experimental studies in assessment of disturbing factors influence on the processes of synaptic plasticity are considered classic protocols of long-term potentiation induction based on the use of high frequency of train stimulation.

The rate of neural network learning is one of the parameters which characterize efficiency and productivity of neural network functioning. The rate of learning in models is determined by time needed for primary single-mode histogram of synaptic conductivities to become bimodal one. Such computer models adequately display real situations in living, but not computerized brain. High frequency of neural network activity and maximal conductivity of all synapses lead to "epileptiform" state, when the rate of learning increases under controlled conditions. The rate of learning decreases in the presence of pathological processes in brain or during uncontrolled use of neurotropic drugs; epileptiform activity accompanied with such motor effects as frank and absence seizures begins to appear in brain.

Therefore, the modelling of processes of biological neural networks functioning under conditions of neuromodulators factors action is promising technique for the development of new neuropharmacological substances action analysis. Above mentioned goes near development of adequate methods of correction of nerve system dysfunctions, because performing of unique calculations is one of brain features. Traditional conservative approaches cannot always afford tools suitable for analysis of biological neural networks functional activity. The time is ripe for integrative analytic approach with computer modelling use including topological approach to explain multisensory neurons functioning as nonlinear chaotic systems

[16, 17].

All neural network structures of the human brain mutually affect the functional state of each other (Figure 2). In addition, apart from the transmission of electrical signals by means of synapses (which ensures the targeting of information transfer) neuro network structures feature a principle of diffuse transmission of information through the intercellular matrix (glial cells and various substances filling the space between the neurons) (Figure 3). Association about the results of such diffuse transmission of information can be felt by anyone who experienced the emotions of unrestrained fear, danger, joy, grief, etc. [18-21].

One more concept of improving efficiency of functioning neural network structures is based on diffuse transmission of signals in the form of hormones, growth factors, cytokines that provide the so-called "emotional coloring" of the actions of neural network structures. By the way, emotional coloring of the process within the brain always features binary polarity as: yes/no, good/bad, safe /dangerous; this feature ensured the choice of appropriate conditions of existence in the process of evolution of living beings and, eventually, to minimize the risk of death. At the final stage of the discussions it makes sense to take a look at the problem of interaction of local neural networks with other neural network structures in the human brain and diversified elements of the surrounding world [23–40] (Figure 4). At this stage of the discussions the didactic warning made by Mary Shelly again rushed back upon us as we do not know what way artificially created neural networks structures (artificial intelligence) will interact with the surrounding human neural network structures. After all, if "yes/no, good/bad" concept has been implemented in the artificial intelligence we can hardly guess now what way the artificial intelligence will treat its creators.

II. Conclusion

For many readers this free style presentation of the ideas may seem rather romantic and narrative. However, the evolution of living nature evidences the survival of those creatures and beings that managed to adapt optimally to the surrounding conditions in the process of their development [8]. Therefore, when solving semantic, intellectual and informational problems at this stage of the development of artificial intelligence and complex semantic systems, it is necessary to look into the future, anticipating wherever possible the consequences of our bold decisions and innovations.

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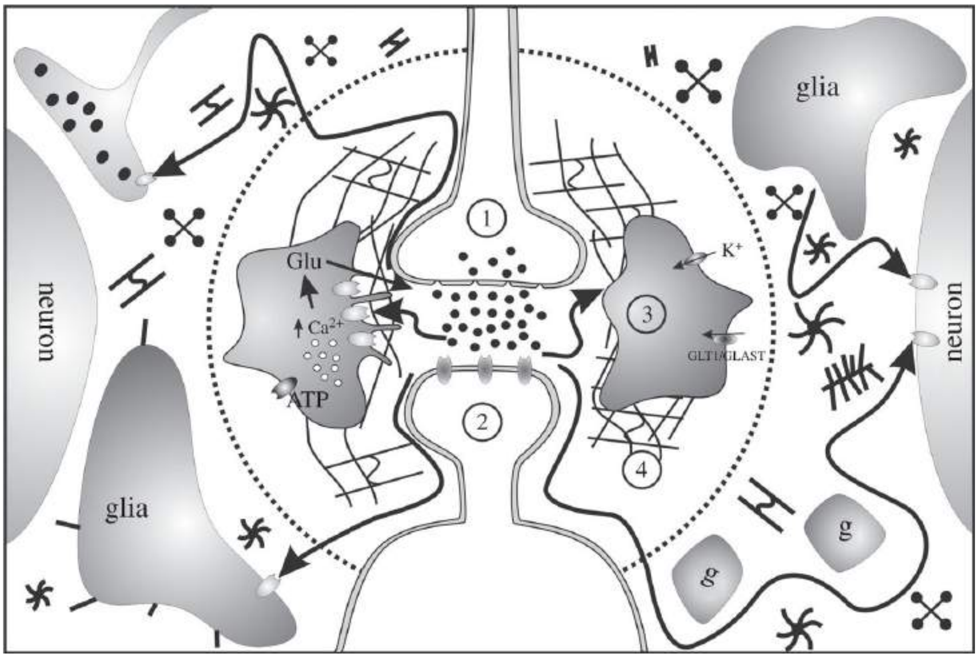

Figure 3. Schematic of intercellular communication via diffusion. Inside the dotted circle: short-distance diffusion of molecules mediates intercellular communication between presynaptic terminal (1), postsynaptic terminal (2) and glia and their processes ensheathing the synapse (3), and it is affected by the ECS properties and its content, particularly the ECM (4). Outside the dotted circle: neuroactive molecules, which have escaped from the synaptic cleft, reach high-affinity neuron or glia receptors at longer distance. This diffusion is restricted to the ECS volume and hindered by neuronal and astrocytic processes and ECM molecules. g, glial processes; Glu, glutamate; GLT1/GLAST, glutamate transporter. Reproduced from [22].

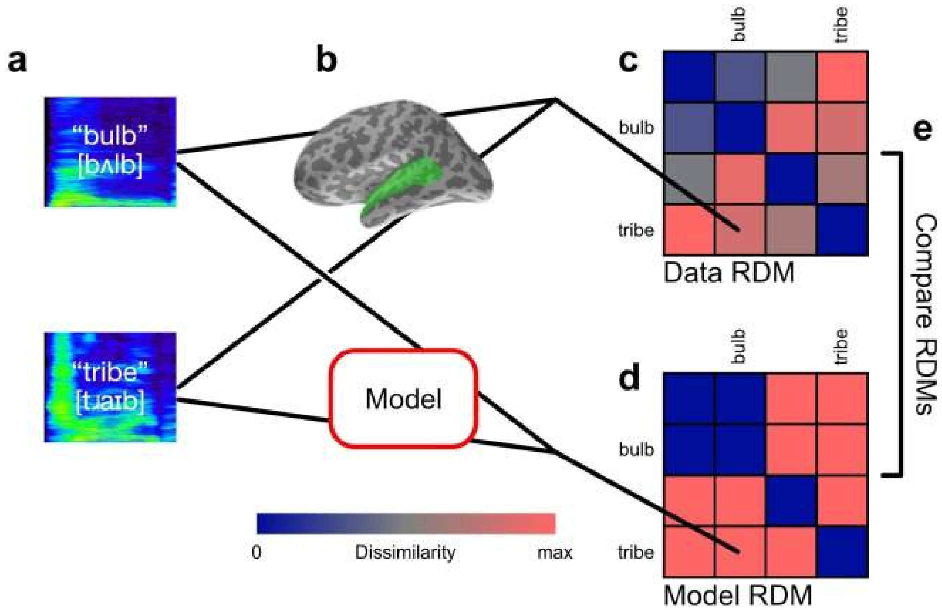

Figure 4. Representational similarity analysis (a) A set of experimental conditions or stimuli are presented to participants. In this example, recordings of English words are presented aurally. (b) For each experimental condition, EMEG data is collected from participants' regions of interest for a specified epoch. (c) Dissimilarities between each pair of responses are computed and stored in a representational dissimilarity matrix. Potential dissimilarity measures include Pearson's correlation distance or Euclidean distance between response vectors. Rows and columns of the matrix are indexed by the condition labels, making the matrix symmetric with diagonal entries all 0 by definition. In this example there are four conditions in total, and the responses to the condition pair (bulb, tribe) is compared, with the value stored in the indicated matrix entry, and its diagonally-symmetric counterpart. (d) A model of the experimental conditions or stimuli is used to compute a model RDM. The model RDM can be computed in several ways, e.g. by comparing representations of the stimuli under the model; or by modelling the dissimilarities directly. (e) Data and model RDMs are statistically compared, e.g. by computing Spearman's rank correlation of their upper-triangular vectors. Reproduced from [34].

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НЕЙРОСЕТЕВЫЕ СТРУКТУРЫ: НАСТОЯЩЕЕ И БУДУЩЕЕ

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Представлены две основные точки зрения на пути создания искусственного интеллекта: разработка на основе тех закономерностей, которые прошла эволюция нейронов естественной нервной системы, и разработка на основе принципиально новых, отличающихся от путей природы закономерностей развития и конструирования нейросетевых структур и программ. Представлены основные структурные элементы будущего искусственного интеллекта, построенного на основе законов развития нейронных сетей человека: основные типы медиаторов и их роль в модуляции информативных сигналов; принцип диффузной передачи информации через межклеточный матрикс; принцип усиления эффективности работы нейросетевых структур за счет диффузной передачи сигналов в форме гормонов, ростовых факторов, цитокинов.

В нейронных сетях мозга человека доминирует принцип передачи сигналов электрическим путем по отросткам нервных клеток. Однако непосредственная акцепция сигнала осуществляется с помощью химических посредников – медиаторов, которые выделяются дискретно, в форме квантов вещества и обеспечивают модуляцию информационных сигналов. Учитывая огромное разнообразие посредников (медиаторов), число которых достигает десятков и сотен тысяч, можно представить огромное количество модулирующих способностей нейронных сетей мозга человека.

Организация нейронных сетей мозга человека всегда включает отдельные популяции нейронных сетей, из которых состоит вся нейросетевая структура мозга человека. Конкретно, в нейросетевой организации присутствуют группы нейронов, которые являются акцепторами сигналов как с периферии, так и внутренних сигналов нейросети. Вторая важная популяция нейронов преимущественно осуществляет обработку поступивших сигналов и принимает решения, которые в форме новых электрических сигналов поступают к популяции нейронов, ответственных за контроль конкретной функции в организме. По обратной связи от рецепторов на периферии, контролирующих эффективность выполнения функции, сигналы поступают в нейронные сети мозга, которые с учетом новой информации осуществляют коррекцию функции.

Все нейросетевые структуры мозга человека взаимно влияют на функциональное состояние друг друга. При этом помимо передачи электрических сигналов с помощью синапсов (что обеспечивает адресность передачи информации) в нейросетевых структурах присутствует принцип диффузной передачи информации через межклеточный матрикс (глиальные клетки и разнообразные субстанции, которые заполняют пространство между нейронами).

Есть еще один принцип усиления эффективности работы нейросетевых структур за счет диффузной передачи сигналов в форме гормонов, ростовых факторов, цитокинов которые обеспечивают так называемую «эмоциональную окраску» действий нейросетевых структур.

Указывается, что при создании искусственного интеллекта исследователи должны не забывать и о негативных последствиях, которые целесообразно предусмотреть и избежать уже на этапах семантического осмысления проблемы.