МАТЕМАТИКА И МАТЕМАТИЧЕСКО ОБРАЗОВАНИЕ, 2025
MATHEMATICS AND EDUCATION IN MATHEMATICS, 2025
Proceedings of the Fifty-Fourth Spring Conference
of the Union of Bulgarian Mathematicians
Varna, March 31 – April 4, 2025

BRAIN-INSPIRED MODELS AND THEIR APPLICATIONS

Petia Koprinkova-Hristova
Institute of Information and Communication Technologies, Bulgarian Academy of Science
e-mail: petia.koprinkova@iict.bas.bg

Even though the contemporary artificial intelligence (AI) became a powerful tool in many areas and even in our everyday life, it still cannot outperform the human brain. The natural intelligence is a result of collaborative work of neural cell ensembles having much more elaborated functionality and connectivity than the artificial neural networks. The paper presents the basic working principles in the brain, neuromorphic computing inspired by them and their applications.

Keywords: artificial intelligence, neural biology, neuromorphic computing

ВДЪХНОВЕНИ ОТ МОЗЪКА МОДЕЛИ И ТЕХНИ ПРИЛОЖЕНИЯ

Петя Копринкова-Христова
Институт по информационни и комуникационни технологии,
Българска академия на науките
e-mail: petia.koprinkova@iict.bas.bg

Въпреки, че съвременния изкуствен интелект (ИИ) стана мощно средство в много области и дори в ежедневието ни, той все още не може да работи по-добре от човешкия мозък. Естествения интелект е резултат от съвместната работа на групи от нервни клетки имащи много по-сложна функционалност и връзки отколкото изкуствените невронни мрежи. Статията представя основните принципи на работа на мозъка, вдъхновените от тях невроморфни изчисления и техни приложения.

Ключови думи: изкуствен интелект, невробиология, невроморфни изчисления

https://doi.org/10.55630/mem.2025.54.018-024

2020 Mathematics Subject Classification: 68Q07, 92C20.

1 Introduction

The contemporary artificial intelligence (AI) relays on artificial neural networks (ANN) inspired by the knowledge about brain structures involved in information processing and decision-making. However, they still do not replicate the brain structure in detail. Although the increased computational power of computers nowadays allows for the implementation of larger and larger ANN models, it is at the expense of enormous energy consumption.

In contrast, our brain possesses computational power of a modern supercomputer having a much more complicated structure in much smaller volume, and consuming much less energy. The current development of neuromorphic architectures opened a new opportunity to replicate brain structures and functionality with lower energy consumption.

This paper presents several basic principles of brain working and its structure on several examples of neuromorphic models and their applications.

2 Brain structure and working principles

Our brain consists of more than 86 billion neural cells [4]. The contemporary neuroscience revealed a lot about their functioning principles and structural connectivity. Figure 1 presents the structure of a typical neural cell briefly called a neuron. It consists of a cell body, dendritic tree and an axon. Each neuron sends information to its neighbors via the axon and receives their signals via its dendrites at connection points called synapses. In ANNs, the neural cell output, y is considered as a sigmoid nonlinear function of the weighted sum of its inputs $x_i, i = 1 \div n$. However, the knowledge from neural biology reveals that the neural cells communicate via sequences of pulses called spikes rather than using continuous signal.

The simplest and widely used spiking neural model is called Leaky Integrate and Fire (LIF) [6] as shown in Figure 2. It considers the cell membrane as a capacitance in an electric circuit. The synapses receive incoming signal as a train of spikes. Each new spike contributes to the total current I in the circuit thus influencing the membrane potential V. When the threshold ϑ is reached the cell emits a spike and returns to its resting state.

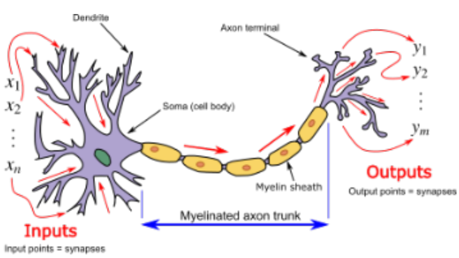

Figure 1. Neural cell structure[1]

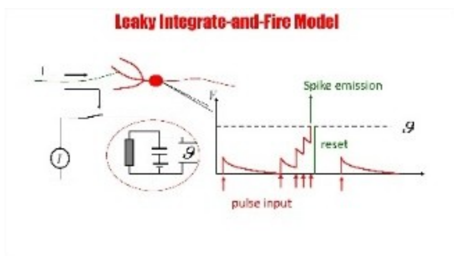

Figure 2. Neuron functionality[2]

[1]By Egm4313.s12 (Prof. Loc Vu-Quoc) - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=72816083.

[2]By Spiking16 - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=97335695.

The moment of spiking of each neuron depends on the frequency of the incoming spikes.

The overall functioning of an ensemble of neural cells depends on the way its individual elements are connected, i.e., on the network topology. In ANNs, the neurons are usually arranged in layers having mainly feedforward connections. In recurrent ANNs (RNNs) feedback connections between layers allow for accounting for past neural states as well. In our brains, the network topology called the connectome, as shown in Figure 3, is rather more complicated allowing for a much more sophisticated way of information processing.

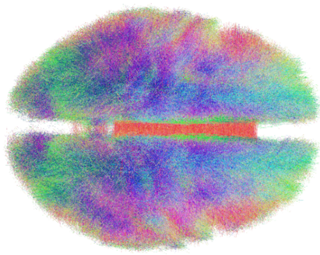

Figure 3. Human brain connectome[3]

The current developments in brain imaging technologies such as Magnetic resonance images (MRI), functional MRI (fMRI) and Magnetoencephalography (MEG) allowed to collect data not only from brain surface, like Electro-encephalographic devices (EEG) but also about deep brain structures, their connectivity and role in sensory information processing and decision-making.

The most important thing, however is to determine not only the topology but also the strength of each connection within a network. It is well known that by proper tuning of these parameters an ANN can learn to mimic quite complicated nonlinear dependence between its input and output variables. However, the ANNs training algorithms are far from the way our brain adapts to the changing environment.

While for ANNs training huge number of examples, computational resources and time are needed, our brain is able to learn from experience in a much faster and energy saving way via a biologically plausible training rule called Spike timing dependent plasticity (STDP) [5]. Figure 4 shows its principles following the Hebbian rule "stable paring of pre- and post-synaptic activity increases the strength of connection".

On this example the pre-synaptic neuron (pre_j) fires before the post-synaptic one (post_i) so the difference between times of spiking $t_j^f - t_i^f$ is negative provoking proportional to it increase of the synaptic strength w^{ij}. If the order of spiking is revers, the synaptic strength should decrease.

Accumulated knowledge about spiking neuron models and brain connectivity allows to develop brain-inspired Spike timing neural network (SNN) models that would be able to solve variety of tasks in the way our brain does. For this aim, there are developed

[3]Andreashorn - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=41581320.

[4]Uploaded work by Bi and Poo (1998) from http://www.scholarpedia.org/article/Spike-timing_dependent_plasticity.

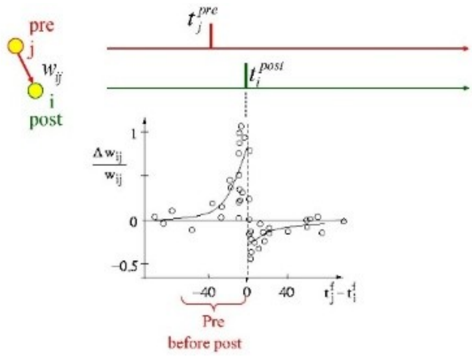

Figure 4. STDP rule[4]

several simulation platforms such as Brian[5], NEURON[6], NEST[7] etc. All these however need huge computational resources to simulate large scale SNN models.

For the aim of accelerating of simulations hardware implementations of SNN models called neuromorphic architectures were recently developed. Some of the most popular are SpiNNaker[8], TrueNorth[9], Loihi[10] etc. These hardware allow for much faster and energy-efficient simulation of large SNN models thus making a step towards their usage in embedded autonomous devices in robotics and many other applications.

3 Examples

Nowadays the brain-inspired models have multiple applications in robotics [1, 2] to enhance robot perception, decision-making, and control; in medicine [8, 12] for precise diagnostics, and neuromorphic sensors; in AI [3, 11] to improve deep learning, pattern recognition, and machine learning and in computing systems [7, 12] via the development of next-generation architectures and large-scale SNNs.

Two of the most important functions of the natural intelligence are to perceive information about the surrounding environment and to make decisions about how to survive in different situations. Here, two examples – of visual information processing and a decision-making system – are presented.

3.1 Visual system

The visual system in our brain, as shown in Figure 5, is widely investigated. Our eyes are the light sensors that transform incoming visual scenes into a neural signal. The photoreceptive cells in the retina detect light changes at each point of the visual scene we observe. They send signals to a deep brain structure called thalamus. It distributes a variety of sensory signals to the areas of the brain cortex for further processing. The part of the thalamus denoted as LGN in Figure 4 is responsible for sending the visual

[5] `https://briansimulator.org/`
[6] `https://www.neuron.yale.edu/neuron/`
[7] `https://nest-simulator.org/`
[8] `https://apt.cs.manchester.ac.uk/projects/SpiNNaker/`
[9] `https://open-neuromorphic.org/blog/truenorth-deep-dive-ibm-neuromorphic-chip-design/`
[10] `https://www.intel.com/content/www/us/en/research/neuromorphic-computing.html`

information to the primary visual cortex V1. There are neurons sensitive to different orientations of objects in the visual scene. Further layers V2 up to MT and LIP areas process the visual information, detecting positions and motions of objects. This process of feature extraction is embedded in the neural cells' specific connectivity. Each cell has so-called receptive field that is the area of the previous hierarchical layer it is connected to. Our brain relays on neurons having variety of receptive fields that filter visual information layer by layer.

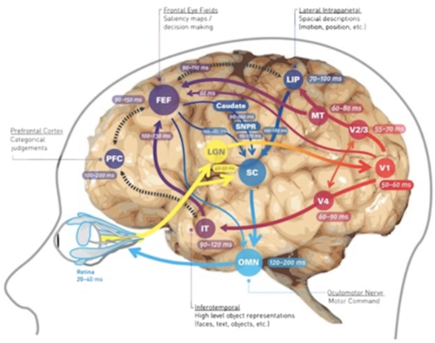

Figure 5. Visual system in the brain[11]

The most complicated visual information processing related to higher level object recognition, decision-making and categorical judgments, is done further in the inferotemporal (IT), frontal eye field (FEF) and prefrontal cortex (PFC), respectively, while deep brain SC area is responsible for sending feedback commands to our eyes via the oculomotor nerve (OMN).

In fact, deep ANNs, like convolutional neural networks (CNN), were inspired by this hierarchical structure. However, unlike CNNs, our brain has a much more complicated connectivity, including feedback and feedforward connections between different hierarchical levels, as well as within them. Besides, the filters in convolutional layers have to be learned by huge number of examples while we are born with a rich bank of natural filters determined by our brain's connectome.

3.2 Decision-making

One of the most important deep structures of our brain is the basal ganglia, shown in Figure 6. It is responsible for the control of precise movements as well as for learning from experience called reinforcement learning (RL). Figure 7 depicts the basal ganglia connectivity with other brain areas. The Striatum area is related to the so-called "value function" in terms of RL theory [10]. Here, we create our "model" of surrounding world in order to predict future outcomes or failures in depending on observations of our environment (sensory information) as well as our previous interactions with it via our actions. The theory states that training of this model is done via the neurotransmitter dopamine that controls the STDP in specific neural connections (dopamine-dependent synapses). Dopamine is produced by the SNc area and it is considered to be the neural analog of

[11] https://www.reddit.com/r/neuro/comments/46saia/delay_of_visual_processing_in_the_human_brain/.

the temporal difference (TD) error in the actor-critic RL scheme [10]. It depends on how well we predicted the next reward or punishment from the environment, i.e., how well we learned our lessons from past experience. The SNr and the recurrent GPe-STN structures are responsible for taking the decision in form “Go / Don’t Go”.

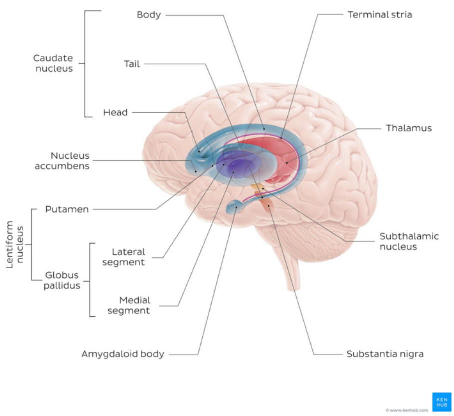

Figure 6. Basal ganglia in the brain[12]

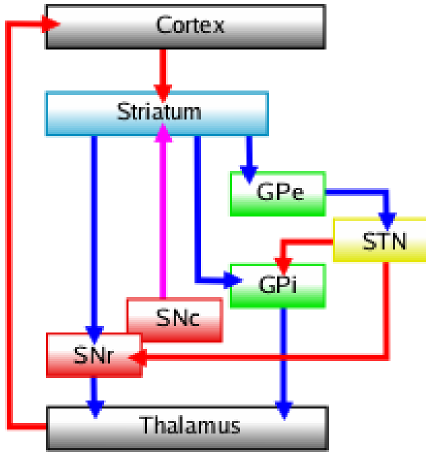

Figure 7. Basal ganglia connectivity[13]

Even though there are developed quite complicated deep RL architectures, they are still not able to outperform our brain’s ability for fast adaptation to changes in our environment.

4 Conclusions

The current developments in neuroscience reveal a lot of our brain secrets how we solve problems in everyday life. The contemporary AI learned how to mimic part of this abilities without going deeper inside brain connectome. The involvement of knowledge about brain’s connectome and learning mechanisms would contribute to develop a new, closer to the natural intelligence AI.

References

[1] M. Barnell, C. Raymond, M. Wilson, D. Isereau, E. Cote, D. Brow., C. Cicotta. Demonstrating Advanced Machine Learning and Neuromorphic Computing Using IBM’s NS16e (2020) *Advances in Intelligent Systems and Computing*, 1228 AISC, pp. 1-11 DOI: 10.1007/978-3-030-52249-0_1

[2] Z. Cai, X. Li. Neuromorphic Brain-Inspired Computing with Hybrid Neural Networks (2021) 2021 IEEE International Conference on Artificial Intelli-

[12] `https://www.kenhub.com/en/library/anatomy/basal-ganglia`.

[13] Created by Andrew Gillies - Own work, CC BY-SA 3.0, `https://commons.wikimedia.org/w/index.php?curid=22686716`.

gence and Industrial Design, AIID 2021, art. no. 9456483, pp. 343-347 DOI: 10.1109/AIID51893.2021.9456483

[3] L. Cheng, Y. Liu. Spiking neural networks: Model, learning algorithms and applications (2018) *Kongzhi yu Juece/Control and Decision*, 33 (5), pp. 923-937 DOI: 10.13195/j.kzyjc.2017.1444

[4] A. Goriely. Eighty-six billion and counting: do we know the number of neurons in the human brain?, Brain, (2024) awae390, DOI: 10.1093/brain/awae390

[5] Guetig et al. Learning input correlations through nonlinear temporally asymmetric hebbian plasticity (2003) *Journal of Neuroscience* 23, pp. 3697-3714 DOI: 10.1523/JNEUROSCI.23-09-03697.2003

[6] E. M. Izhikevich. Simple Model of Spiking Neurons IEEE Transactions on Neural Networks (2003) 14, pp. 1569-1572

[7] J. Liu, H. Wu. Research hotspots and trends of brain-inspired intelligence (2021) *Chinese Journal of Biomedical Engineering*, 40 (1), pp. 91-98

[8] Y. Lv, H. Chen, Q. Wang, X. Li, C. Xie, Z. Song. Post-silicon nano-electronic device and its application in brain-inspired chips (2022) *Frontiers in Neurorobotics*, 16, art. no. 948386 DOI: 10.3389/fnbot.2022.948386

[9] K. Roy, A. Jaiswal, P. Panda. Towards spike-based machine intelligence with neuromorphic computing (2019) *Nature*, 575 (7784), pp. 607-617 DOI: 10.1038/s41586-019-1677-2

[10] R. S. Sutton, A. G. Barto. Reinforcement Learning: An Introduction, Second Edition, MIT Press, Cambridge, MA (2018)

[11] R.-D. Wang, R. Wang, T.-D. Zhang, S. Wang. A Survey of Research on Robotic Brain-inspired Intelligence (2024) *Zidonghua Xuebao/Acta Automatica Sinica*, 50 (8), pp. 1485-1501 DOI: 10.16383/j.aas.c230705

[12] Y. Wang, J. Lu, M. Gavrilova, R. A. Fiorini, J. Kacprzyk. Brain-Inspired Systems (BIS): Cognitive Foundations and Applications (2018) Proceedings - 2018 IEEE International Conference on Systems, Man, and Cybernetics, SMC 2018, art. no. 8616173, pp. 995-1000 DOI: 10.1109/SMC.2018.00177