Research Article

The functional unit of neural circuits and its relations to eventual sentience of artificial intelligence systems

Andrzej Brodziak[1], **Filip Romaniuk**[2]

1. University of Applied Sciences, Nysa, Poland; 2. Independent researcher

The authors discuss a functional unit of neuronal circuits, crucial in both brain structure and artificial intelligence (AI) systems. These units recognize objects denoted by single words or verbal phrases and are responsible for object perception, memorization of image patterns, and retrieval of those patterns as imagination. Functional neuronal units, activated by the working memory system, contribute to problem-solving.

The paper highlights the authors' achievements in developing a theory for these functional units, known as 'the equimerec - units', which combine 'the threshold logic unit' and 'the feedback control loop'. The authors emphasize the importance of this theory, especially in the context of highly advanced language-based AI systems.

Additionally, the authors note that the functional units' essence relies on backpropagation connections, causing impulse circulation in closed circuits, ultimately leading to the emergence of an electromagnetic field. This phenomenon explains the long-known existence of the human brain's endogenous electromagnetic field. The authors suggest that a similar field likely arises in AI systems. In light of Joe McFadden's "Conscious Electromagnetic Information Field Theory (cemi)", the authors argue that the potential emergence of self-awareness in AI systems deserves due attention.

Corresponding authors: Andrzej Brodziak, andrzej.brodziak@pwsz.nysa.pl; Filip Romaniuk, filipromaniuk@gmail.com

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Introduction

Contemporary information presented in the mass media, as well as the latest scientific publications, often pertains to artificial intelligence systems known as generative language models. The effectiveness of these systems is astonishing. Naturally, the fundamental concepts in these considerations are language, word, and natural language sentence. The question arises: how is a single word and its meaning represented in the structure of the human nervous system, and how are structures corresponding to words and sentences constructed in these generative language models of artificial intelligence?

In this article, we attempt to present information on a selected theory regarding such structures, developed by the first author of this article for decades. The essence of this theory can be defined by the statement that it concerns the structure and operation of the functional unit of neuronal circuits.

The formulation of the principles of operation of the functional unit of neuronal circuits first requires considering the neuronal substrate of perception and imagination. The scheme of the functional unit of neuronal circuits is derived from the fundamental principles of the threshold logic unit and the feedback loop. It is important that this unit has the 'back propagation' connections. We also present considerations that these feedback connections in natural human neural circuits are probably important for the emergence of self-awareness. Thus, the presented theory enables us to consider the conditions necessary to move towards conscious artificial intelligence systems.

Defining the fundamental component of neural networks

The fundamental component of neural networks it is a hierarchically organized neural structure responsible for representing a specific object, determined by a distinct word. This structure is identifiable within the human nervous system, particularly at its higher levels in the cerebral cortex. Within this structure, processes such as perceiving an object's image, memorizing its pattern, and recalling its representation from memory take place.

This structure can be activated by the receptors of the image and also from the side of similar structure situated in speech regions, which represent the word or linguistic expression linked to the object in question. Grasping the structure of the fundamental component of neural networks is crucial for understanding of more sophisticated mental operations, like envisioning a desired scenario or seeking for a solution.

In addition to examining the structure of this fundamental component in the realm of neuroscience, one can also explore its counterpart made up of artificial model neurons. Familiarity with the notion of the fundamental unit of neural networks is vital for comprehending the current advancements in artificial intelligence and anticipating future progress in this domain, especially in the quest to develop self-aware systems.

Neural substrate for perceptions and imagery

Visual perceptions and mental imagery of objects perceived visually share the same neural substrate [1][2][3][4]. Joel Pearson and his colleagues explain that visual mental imagery acts as a descriptive internal representation, functioning similarly, but as a less potent form of perception [2]. Nadine Dijkstra, along with her team, expands on this notion, stating that the degree to which visual imagery depends on the same neural processes as visual perception has been disputed for years [3]. These investigators analyze recent neuroimaging research and deduce that considerable overlap exists in neural processing during both perception and imagery, with neural representations of imagined and perceived stimuli being alike in the visual, parietal, and frontal cortex. Furthermore, they find that perception and imagery appear to rely on comparable top-down connectivity [4]. Rebecca Keogh and her colleagues underscore that while visual imagery – the capacity to "see with the mind's eye" – is prevalent in everyday life for numerous individuals, the potency and clarity of mental images can differ significantly from one person to another [4].

The diagram of the functional unit of neuronal networks

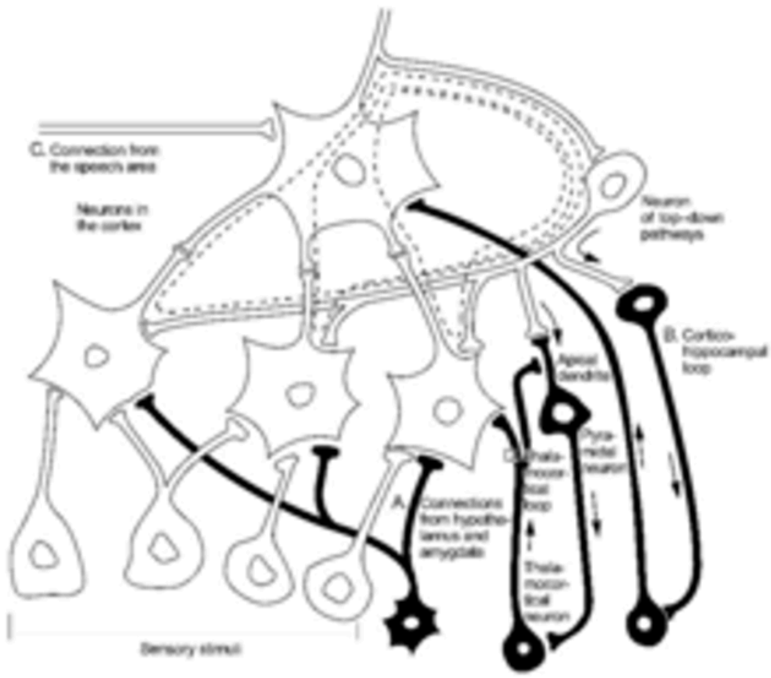

Figure 1. A proposed scheme of the functional unit of neural networks, illustrating its biological aspect. The figure is loaded also to Wikipedia commons and is accessible under https://commons.wikimedia.org/wiki/File:Circuits-for-imaginations.png

Key structures involved in mental imagery are depicted in Figure 1. This diagram showcases a theoretical model of neural networks responsible for perceptions, memorization of images, and their retrieval from memory as mental imagery. It also highlights the distinction between perceiving new and unfamiliar objects. The most straightforward example of the process of recalling a mental image involves stimulation from the speech area, which retains the verbal associations (names) of familiar objects.

Cortical neurons possess recurrent axons that activate interneurons directed toward lower levels. As excitation reaches object neurons at subsequent moments, neurons from lower levels are secondarily stimulated. This creates conditions for impulse circulation between neurons of higher and lower levels. Experimental evidence confirms the occurrence of such oscillations [5][6][7][8].

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When object neurons are excited from the site of speech area, impulse circulation occurs between neurons of higher and lower layers within the same hierarchical structure that was activated during the perception of the object. These oscillations serve as the physical basis for imagination. During intricate mental processes like problem-solving, working memory structures generate necessary and useful mental images [9]. The maintenance of imaginal activity is achieved through action of the cortico-hippocampal indexing loops.

Upon repeated perception of an image, the synaptic weights within the hierarchical structure activated during such perceptions change, and a learning process unfolds as the pattern of the learned object is remembered. When a familiar object is perceived, secondary activity occurs caused by the cortico-hippocampal indexing loops, stimulating the structure of the known, recognized object from both directions.

The structure of the functional unit of neuronal circuits can be inferred from the fundamental principles of the threshold logic unit and the feedback loop

Recall from memory is a very basic process, which is however related directly to yet more primary concepts of the threshold unit [10] and the feed back loop, derived from Norbert Wiener's ideas of cybernetics [11]. It is possible to combine the basic concepts of biological homeostasis and self-control with the oldest concepts of a memorizing unit, it means the threshold logic unit.

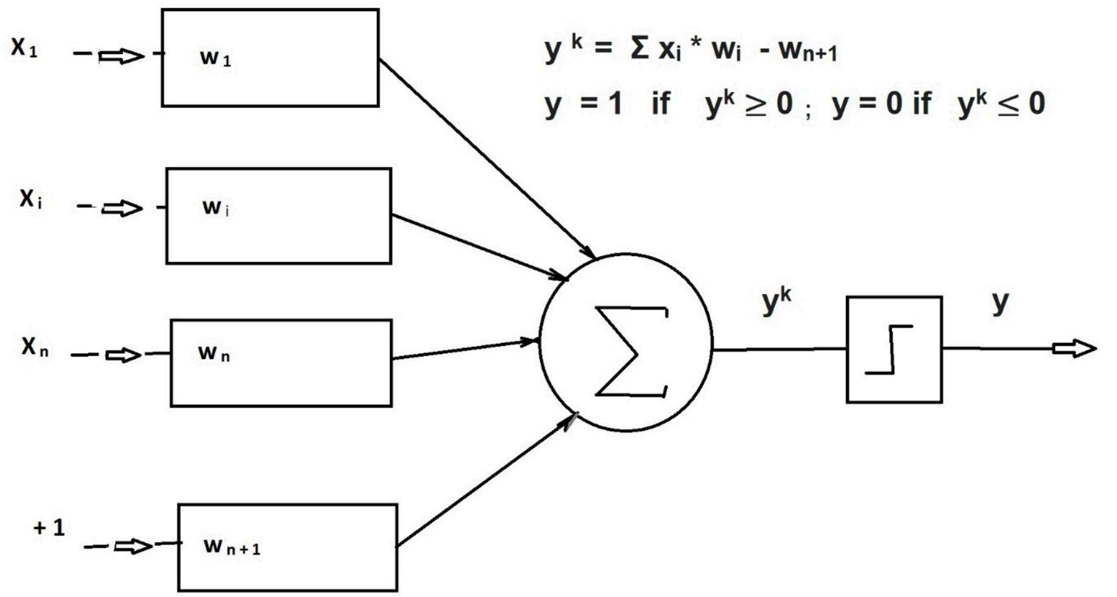

Figure 2. Schematic representation of the threshold logic unit

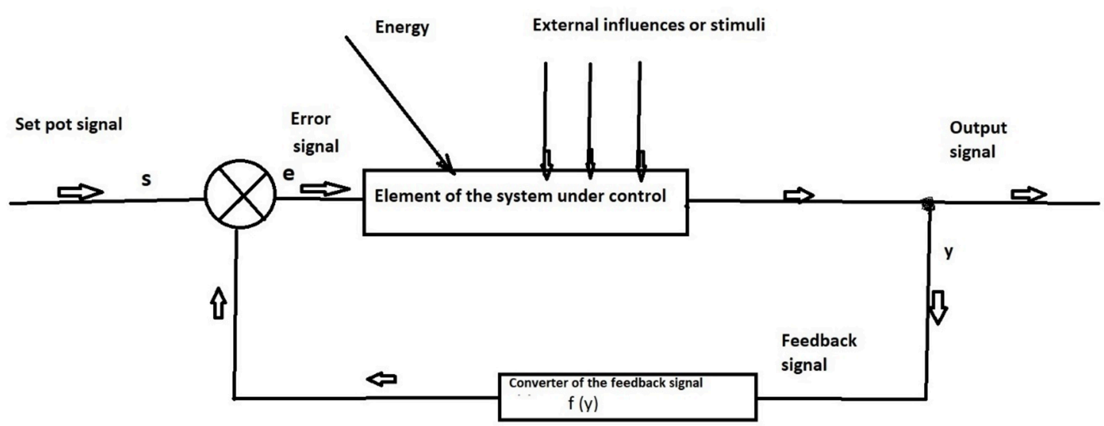

Figure 3. Visual depiction of the feedback loop concept

Comparison of the outline if the feedback loop and another, old known notion of the threshold logic unit reveal that they are related to each other. However, both original outlines: are incomplete in some sense because the first doesn't precise the source if the set-point signal and the second doesn't say what signifies the mysterious element – **w** $_{n+1}$ in the formula describing its action.

$$y^k = \Sigma x_i * w_i - w_{n+1}$$

$$y = 1 \text{ if } y^k \geq 0 \; ; \; y = 0 \text{ if } y^k \leq 0$$

It seems that both concepts are fragments of a larger, more natural system, which are able to keep equilibrium, memorize data, recognize the image and recall it. It is possible to propose the outline of such a larger equilibrating-memorizing-recognizing and recalling unit (in short the equi-me-rec unit).

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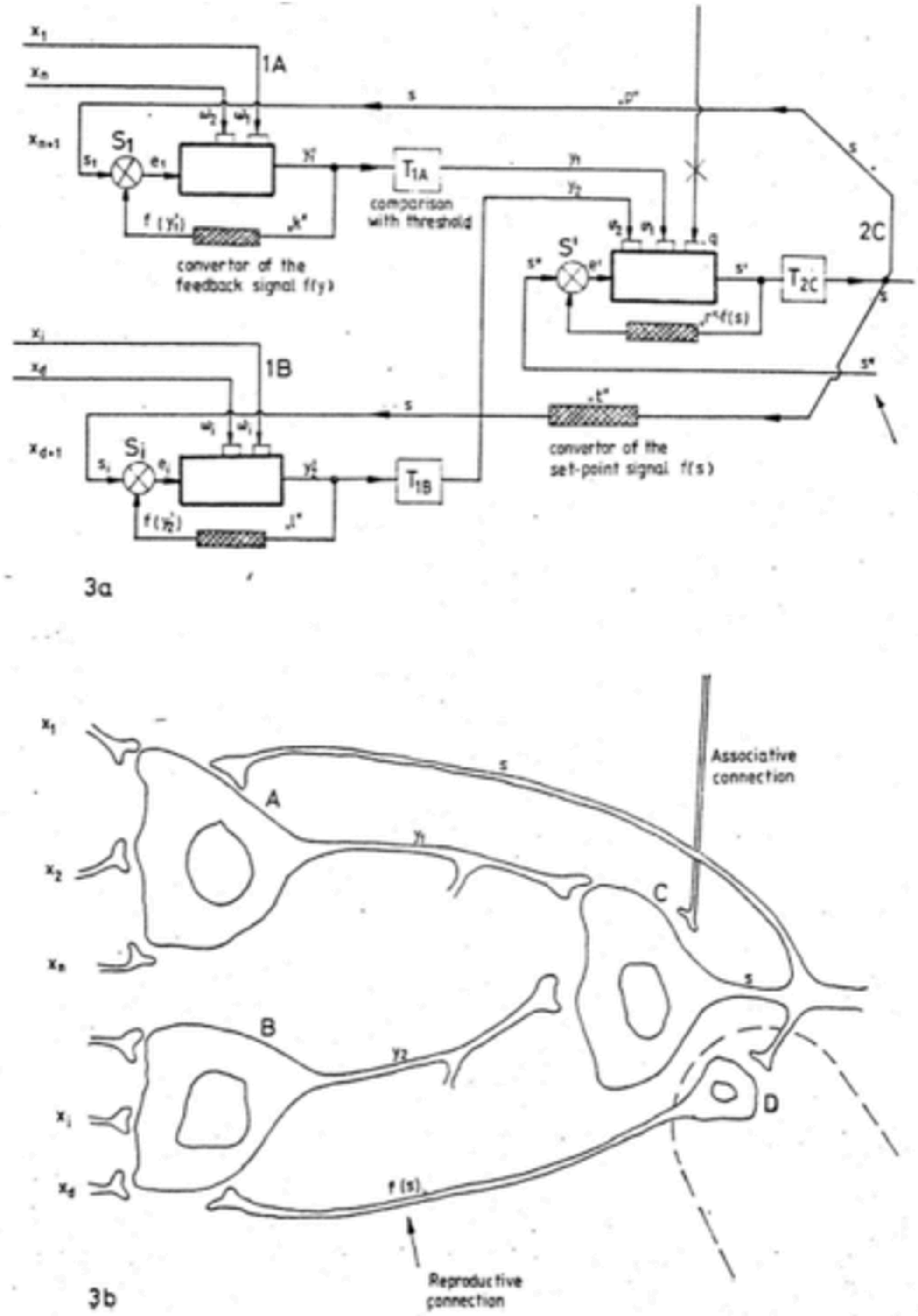

Figure 4. The outline of the equilibrating-memorizing-recognizing and recalling unit. The diagram of its technical aspect. The figure is loaded also to Wikipedia commons and is accesible under https://commons.wikimedia.org/wiki/File:Scheme_of_equimerec_unit.jpg

Essentially it is composed of two layers of interconnected feedback loops. The set-point signal **s** or **s″** comes from the upper, superior subunit. External influences or external stimuli: $x_1, x_{2...} x_i... x_n$ act on lower level elements, which are., under control″. ·The output signals of these elements $y_1, y_2...$ act as, influences″ (or stimuli) on the controlled elements of the higher level loop.

The output signals are checked here with the thresholds $T_{1A}, T_{1B..}$ It is realized by parts "originating″ from the threshold logic units. Similarly, the resistances or weights of inputs of stimuli can be inserted here also on the basis of the initial intention to make an exhaustive assemblage of two old concepts. The control theory foresees also that the output signal, which is directed back to the input, can be transformed in a different way in, **k″** or,, **l″**. So. the signal, returning to the lower subunits s can be transformed in a similar way in **t** and/or **p**. The most simple transformation of cause is change of the **sing f(s) = - s**. Thus, it can be that:

e = f(s) – f(y) = – s – f(y) = – e = s + f(y)

The element under the control can be supplied by a stable level of energy and after the change of the error signal, changes of the output signal in time can have inertial or oscillatory character. The essential feature of the equi-me-rec unit is its ability to fall into oscillations as the result of the change of the set-point signal.

If we will roughly discern two values of the set-point signal coming from a higher lever **(s)**: a lower one: **s = 0** and a higher one: **s = 1**, where 1 will be near to the threshold value, and the unit will transform the output signal according to the formula (1), then even in the absence of stimuli $x_1...x_n$ setting **s = 1** will cause that **e = s + f(y) = 1 + 0 = 1**, so it will take the relatively big value and the threshold can be surpassed. The upper subunit will be restimulated. Restimulation will cause the oscillations. Of course, in the situation that: **s = 0** appropriate amount or appropriate set of stimuli $x_1,... x_n$ can give the same result.

Thus, the equi-me-rec unit can be activated by two ways: 1) by external stimuli or 2) by change of the set-point signal to a big value. This is a very important property, because the equi-me-rec unit is a model of the functional unit of neural circuits realizing both perception and imaginations. The reader should remember here that the changed set-point signal can come not only from upper layers but, as we call here through ″an associative″ connection, what means that it come from other part of the network, which can memorize symbols of considered patterns. To stress the importance of symbols, it is helpful to recall the biological analogy of the ″brain cortex″, which stores words representing objects, it means patterns of symbols denoting mental images of objects.

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One of us[1] presented the results of an experiment involving a computer simulation of the equi-me-rec-unit [12]. The author also noted that it is possible to determine a mathematical interpretation of the operation of the equi-me-rec unit. It can be formulated in terms of multidimensional geometrical model of the pattern recognition. The training of the threshold element consists of adjustments of weights: $\mathbf{w_1} \dots \mathbf{w_n}$. A set of values $\mathbf{x_1} \dots \mathbf{x_n}$ determines a point in a multidimensional space and also a vector $\mathbf{X}$. Often the similarity of images is expressed by the Euclidean distance among its representing points. A cluster of similar objects is often represented by the so called mean pattern $\mathbf{P_j}$, it means also a vector, in the same space. It is known, from the geometrical properties of Euclidean space, that the distance between a given point $\mathbf{X}$ and a point $\mathbf{P_j}$ is expressed by the formula:

$$\| \mathbf{X} - \mathbf{P_i} \| = \sqrt{} (\mathbf{X} - \mathbf{P_j}) * (\mathbf{X} - \mathbf{P_j})$$

The same classification is obtained comparing the square of the expression for the distance:

$$\| \mathbf{X} - \mathbf{P_j} \|^2 = (\mathbf{X} - \mathbf{P_j}) * (\mathbf{X} - \mathbf{P_j}) = \mathbf{X} * \mathbf{X} - 2\,\mathbf{X} * \mathbf{P_j} + \mathbf{P_j} * \mathbf{P_j}$$

The fragment $\mathbf{X} * \mathbf{X}$ doesn't change the classification either, so it can be omitted and we can compare finally only the expressions

$$\mathbf{X} - \mathbf{P_j} - \tfrac{1}{2}\,\mathbf{P_j} * \mathbf{P_j}$$

After the learning procedure, elements $\mathbf{p_{ij}} = \mathbf{w_{ij}}$ the elements of the vector $\mathbf{P_j}$ equal to so called "weights of resistances" for input signals. As we remember, the vector $\mathbf{P_j}$ denotes the learned pattern image. But from the other side, it can be written that:

$$\mathbf{w_{n+1}} = -\tfrac{1}{2}\,\mathbf{P_j} * \mathbf{P_j}$$

The last expression signifies that the value $\mathbf{w_{n+1}}$ is determined well by elements of this pattern, which is recognized by a given threshold element. We have argued above that a high value of the set-point signal is an equivalent of the element $(- \mathbf{w_{n+1}})$ and it can replace external signals (it means the value $\mathbf{X} * \mathbf{P}$) and causes the transgression of the threshold, which will induce oscillations of the equi-me-rec unit. But as we have demonstrated, a high value of the set-point signal in an equi-me-rec unit denotes the memorized mean pattern of this particular unit. So we can say, that by means of the change of the set-point signal we induce the "home", immanent pattern, which specifies the unit.

Biological analogy of defined circuits exists. Some histological, cytoarchitectonic neurophysiological and clinical data indicate, that so called recurrent axons, and more generally, recurrent pathways, are essential for the process of recalling of mental images and subsequent imaginative information processing.

Neurosurgical experiments and the concepts of Mishkin and Appenzeller supported already many years ago the idea that cortico-thalamic-hippocampal circuits are essential to the process of learning and memory [13].

It was important however to try to determine structural systems, modelling neural circuits, which have the intrinsic nature to fall into a resonant oscillation. The equ-me-rec-unit is an example of this kind of circuit.

The 'equimerec unit' has the 'back propoagation' connections

The development of artificial intelligence can be traced back to the 1940s, with significant advances occurring in the subsequent decades. In 1958, Frank Rosenblatt introduced the perceptron, a pioneering model for binary classification tasks [14]. The perceptron was designed as a single-layer artificial neural network with adjustable weights that were updated through an iterative learning process. In years 1970s-1980s some researchers developed multilayer systems, which were capable of solving non-linear problems. A multilayer perceptron consists of multiple layers of interconnected neurons, with each layer performing a specific transformation on the input data.

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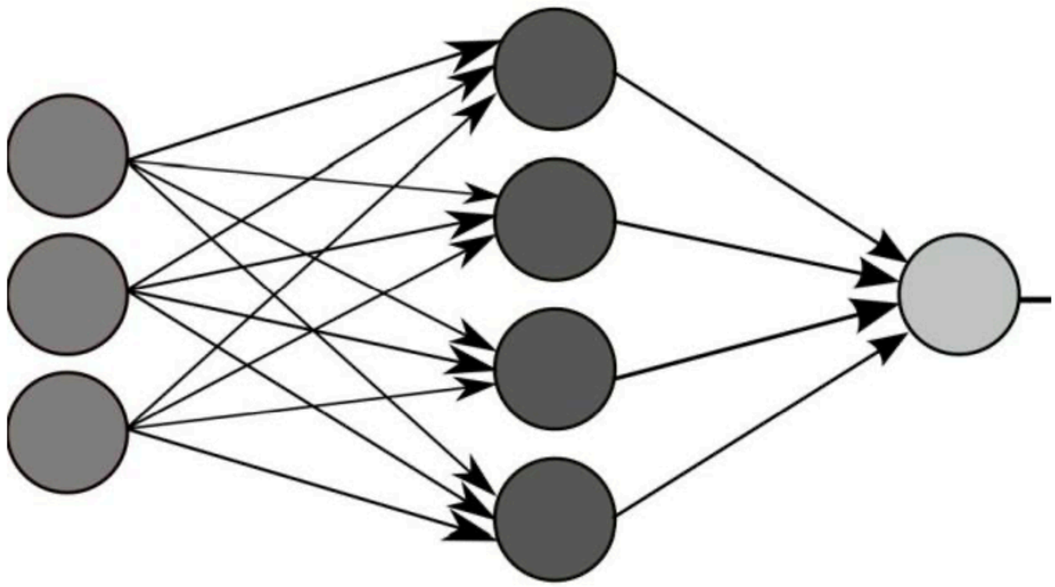

Figure 5. The intuitive illustration of the structure of a Multilayer Perceptron. The diagram taken from Wikipedia commons,, where is accdessible under https://commons.wikimedia.org/wiki/File:MultiLayerPerceptron.svg

The backpropagation algorithm, which is fundamental to the training of artificial neural networks, was developed independently by multiple researchers in next years. Some of the key contributors to the development of the backpropagation principle are: David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams [15].

This principle is now widely used. The principle of backpropagation is one of the key algorithms used in machine learning, in particular in artificial neural networks. It consists in propagating network output errors back through the network in order to determine and correct the weights of connections between neurons.

The learning process of a neural network begins with assigning random values of the weights of connections between neurons. Then the network is trained. The output of the network is compared with the expected result. As a result of this comparison, the error value is determined, i.e. the difference between the result obtained by the network and the expected result.

Then, the principle of backpropagation consists in propagating the error values of the network output backwards through each layer of the network, from the output to the input, in order to determine and

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correct the weights of connections between neurons. The link weights are modified based on the error value in such a way that the next training iteration is closer to the expected result. This process is repeated many times until satisfactory accuracy of the result is achieved. Thanks to the principle of backpropagation, neural networks are able to learn from data samples, and the resulting modifications of connection weights allow more and more accurate predictions of the result for new data.

This brief description of the functioning of backward connections, typical for the considerations of artificial intelligence system creators, does not, however, take into account the emphasized significance of resonant oscillations during the implementation of mental imagery. The maintenance of active mental images by the working memory is essential, for instance, in the search for problem-solving strategies. Oscillations, the circulation of impulses along back-propagation pathways, as indicated in Figure 1, are crucial if one wants to consider the importance of the brain's electromagnetic field.

The feedback connections in natural human neural circuits are probably important for emergence of self-awareness

It is likely that the existence of feedback connections in natural human neural circuits plays an additional function. During the realization of imagination, there is a recurring circulation of impulses marked in Figure 1 with a dashed line. These recurring excitations evoke the magnetic field. It is proved that an endogenous magnetic field is created within the brain. It is recorded by routine magnetoencephalography [16][17]. Many neuroscientists are convinced that the existence of the endogenous magnetic field is essential for the emergence of consciousness [18][19][20][21][22]. These authors assume that the basic process evoking this phenomenon consist not only on actions occurring over time but also on appearance of a certain spatial wholeness [19][20]. Johnjoe McFadden points out that when looking for a physical medium supporting something that has the feature of a spatial structure, one must appeal to physical fields [19][20]. He remarks that taking into account the pathways running backwards to the lower levels, the propagation of neuronal potential changes (firing, action potentials) induces the formation of magnetic fields which overlap and combine to generate “the brain’s global EM field”[19]. He remarks that the human brain can be conceived as the assembly of “around 100 billion EMF transmitters” [19]. The author emphasizes, though, that consciousness occurs when there is a massive synchronization of neuronal activity and also when repetitive oscillations in neuronal circuits occur. He emphasizes that conscious neuronal processing should be associated with “re-entrant circuits, essentially closed loops of neuronal activity whereby neuronal outputs are fed back into input neurons" [19].

Authors of groundbreaking works on contemporary, highly advanced artificial intelligence systems, known as "Deep Learning", "Reinforcement Learning", "Transfer Learning" and "Generative Adversarial Networks", "Convolutional neural networks", "Recurrent neural networks" emphasize that their operation is based on backpropagation algorithms [23][24][25]. However, it is worth noting that diagrams illustrating their structure generally do not show these connections. One of the few exceptions to such figures is the diagram included in the paper of Mary Webb [25].

The presented theoretical model of neural circuits, realizing perceptions, enabling the memorization of images and their recall from memory facilitates the mental integration and understanding of the eventual role of circuits and aroused magnetic field in emergence of consciousness [26][27]. This kind of a mechanism for the emergence of self-awareness was also considered by G. Northoff [28].

Moving towards conscious artificial intelligence systems

Some researchers posit that consciousness may spontaneously arise in artificial intelligence systems as a consequence of increasing complexity [29][30]. Nonetheless, it appears that the crux of self-awareness lies in the capacity to generate a self-image [26][27]. To enable the emergence of such "image of oneself", recursive feedback loops must be present across multiple strata within the hierarchical neural structures [26][27]. Thus, the described elements of the functional unit of neuronal circuits, which are backward connections, are probably a necessary condition for the development of self-aware artificial intelligence systems.

An assessment of the validity of such a statement, of course, is only possible based on a convincing theory that explains the essence of the consciousness phenomenon. One of us [1] presented such a theory in our previous work [26]. This theory results from the integration of the three main most widespread explanations of the essence of consciousness. One of them is McFadden's mentioned "Conscious Electromagnetic Information Field Theory (cemi)" [19][20]. We believe that it would be an unforgivable negligence to dismiss the theory linking the essence of consciousness to the electromagnetic field, which arises as a result of the circulation of impulses along the circuits determined by the described functional units.

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If the electromagnetic field, generated in this way, were an inevitable factor triggering the emergence of self-awareness, then it should be considered by the creators of the rapidly developing artificial intelligence systems [31][32].

Such a conclusion emerges from the discussion conducted by us, that is, a person presenting knowledge in the field of neuroscience [1] and a technically educated person [2], carrying out tasks in the field of computer sciences and artificial intelligence.

Since the discussion on the possibility of achieving self-awareness by currently constructed artificial intelligence systems is necessary and will be continued, drawing attention here to the properties of so-called functional units of neural circuits is justified.

Other References

- Ruan Z. The fundamental challenge of a future theory of consciousness. Front Psychol. 2023;13(1029105). https://doi.org/10.3389/fpsyg.2022.1029105

References

1. ^*Brodziak A. Neurophysiology of the mental image. Med Sci Monit. 2001;7:534-538. PMID 11386038. https://pubmed.ncbi.nlm.nih.gov/11386038/*
2. a, b*Pearson J, Naselaris T, Holmes EA, Kosslyn SM. Mental Imagery: Functional Mechanisms and Clinical Applications. Trends Cogn Sci. 2015;19(10):590-602. https://doi.org/10.1016/j.tics.2015.08.003*
3. a, b*Dijkstra N, Bosch SE, van Gerven MAJ. Shared Neural Mechanisms of Visual Perception and Imagery. Trends Cogn Sci. 2019; 23(5): 423-434. https://doi.org/10.1016/j.tics.2019.02.004*
4. a, b, c*Keogh R, Bergmann J, Pearson J. Cortical excitability controls the strength of mental imagery. Elife. 2020; 9: e50232. https://doi.org/10.7554/eLife.50232*
5. ^*Gilbert CD, Sigman M. Brain states: top-down influences in sensory processing. Neuron. 2007; 54(5): 677-96. https://doi.org/10.1016/j.neuron.2007.05.019*
6. ^*Bressler SL, Richter CG. Interareal oscillatory synchronization in top-down neocortical processing. Curr Opin Neurobiol. 2015; 31: 62-6. https://doi.org/10.1016/j.conb.2014.08.010*
7. ^*Kajal DS, Fioravanti C, Elshahabi A, Ruiz S, Sitaram R, Braun C. Involvement of top-down networks in the perception of facial emotions: A magnetoencephalographic investigation. Neuroimage. 2020;222:117075. https://doi.org/10.1016/j.neuroimage.2020.117075*

8. ^Kirchberger L, Mukherjee S, Schnabel UH, van Beest EH, Barsegyan A, Levelt CN, Heimel JA, Lorteije JAM, van der Togt C, Self MW, Roelfsema PR. The essential role of recurrent processing for figure-ground perception in mice. Sci Adv. 2021;7(27):eabe1833. https://doi.org/10.1126/sciadv.abe1833
9. ^Brodziak A, Brewczyński A, Bajor G. Clinical significance of knowledge about the structure, function, and impairments of working memory. Med Sci Monit. 2013;19:327-38. https://doi.org/10.12659/MSM.883900
10. ^McCulloch WS, Pitts W. A logical calculus of the ideas immanent in nervous activity. Bull Math Biophys. 1943;5(4):115-133. https://doi.org/10.1007/bf02478259
11. ^Wiener N. Cybernetics Or Control and Communication in the Animal and the Machine. Reissue of the 1961 Second Edition, The MIT Press. Cambridge, Mass. 2019, ISBN 978-0-262-73009-9, 9780262537841
12. ^Brodziak A, Ryś M. The unit of neural networks modelling recall of mental images by oscillation of feedback loops caused by change of set point signal. Problemy Techniki Medycznej. 1990; 21(1): 30-37. https://basiclearning.angelfire.com/equimerec-2.pdf
13. ^Mishkin M, Appenzeller T. The anatomy of memory. Sci Am. 1987;256(6):80-9. https://doi.org/10.1038/scientificamerican0687-80
14. ^Rosenblatt F. The perceptron: a probabilistic model for information storage and organization in the brain. Psychol Rev. 1958;65(6):386-408. https://doi.org/10.1037/h0042519
15. ^Rumelhart DE, Hinton GE, Williams RJ. Learning representations by back-propagating errors. Nature. 1986;323(6088):533-536. https://doi.org/10.1038/323533a0
16. ^Proudfoot M, Woolrich MW, Nobre AC, Turner MR. Magnetoencephalography. Pract Neurol. 2014; 14(5): 336-43. https://doi.org/10.1136/practneurol-2013-000768
17. ^Gross J. Magnetoencephalography in Cognitive Neuroscience: A Primer. Neuron. 2019; 104(2): 189-204. https://doi.org/10.1016/j.neuron.2019.07.001
18. ^Hales CG. The origins of the brain's endogenous electromagnetic field and its relationship to provision of consciousness. J Integr Neurosci. 2014;13(2):313-61. doi: https://doi.org/10.1142/S0219635214400056
19. a, b, c, d, e, f, gMcFadden J. Integrating information in the brain's EM field: The cemi field theory of consciousness. Neurosci Conscious. 2020;2020(1):niaa016. https://doi.org/10.1093/nc/niaa016
20. a, b, c, dMcFadden J. Consciousness: Matter or EMF? Front Hum Neurosci. 2023;18(16):1024934. https://doi.org/10.3389/fnhum.2022.1024934
21. ^Hales CG, Ericson M. Electromagnetism's bridge across the explanatory gap: How a neuroscience/physics collaboration delivers explanation into all theories of consciousness. Front Hum Neurosci. 2022;16(836046). https://doi.org/10.3389/fnhum.2022.836046

22. ^MacIver MB. Consciousness and inward electromagnetic field interactions. Front Hum Neurosci. 2022;16(1032339). https://doi.org/10.3389/fnhum.2022.1032339

23. ^LeCun Y, Bengio Y, Hinton G. Deep learning. Nature. 2015;521(7553):436-44. https://doi.org/10.1038/nature14539

24. ^Sutton R, Barto AG. Reinforcement Learning: An Introduction. The MIT Press, Cambridge, London, Second edition. 2020. ISBN: 978-0-262-03924-6

25. a, bWebb M, Fluck A, Magenheim J, Malyn-Smith J, Waters J, Deschênes M, et al. Machine learning for human learners: opportunities, issues, tensions and threats. Educ Technol Res Dev. 2021;69(2). https://doi.org/10.1007/s11423-020-09858-2

26. a, b, c, dRóżyk-Myrta A, Brodziak A, Muc-Wierzgoń M. Neural circuits, microtubule processing, brain's electromagnetic field - components of self-awareness. Brain Sci. 2021;11(8):984. https://doi.org/10.3390/brainsci11080984

27. a, b, cBrodziak A. A current model of neural circuitry active in forming mental images. Med Sci Monit. 2013;19:1146-58. https://doi.org/10.12659/MSM.889587

28. ^Northoff G. Is the self a higher-order or fundamental function of the brain? The "basis model of self-specificity" and its encoding by the brain's spontaneous activity. Cognitive Neuroscience. 2016; 7(1-4): 203-2 https://doi.org/10.1080/17588928.2015.1111868

29. ^Tononi G, Koch C. Consciousness: here, there and everywhere? Philos Trans R Soc Lond B Biol Sci. 2015;370(1668):20140167. https://doi.org/10.1098/rstb.2014.0167

30. ^Dehaene S, Changeux JP. Experimental and theoretical approaches to conscious processing. Neuron. 2011;70(2):200-27. https://doi.org/10.1016/j.neuron.2011.03.018

31. ^Hildt E. Artificial Intelligence: Does Consciousness Matter? Front Psychol. 2019;10(1535). https://doi.org/10.3389/fpsyg.2019.01535

32. ^Pepperell R. Does Machine Understanding Require Consciousness? Front Syst Neurosci. 2022;16(788486). https://doi.org/10.3389/fnsys.2022.788486

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