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Learning And Memory Issues In Neuromorphic Engineering: A Review

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Abstract

Brain is the most complex computing device which performs the high level cognitive functions such as pattern classification, recognition etc., with high efficiency and low power consumption. Neuromorphic Engineering takes the lessons from biological systems and try to emulate such circuits in the sate-of-art of current microelectronics. On chip learning has been pursued intensively by neuromorphic researchers. Any system which is capable of Learning and Adapting is said to be Intelligent. The Bio-inspired architectures of Neuromorphic VLSI Chips aim towards Intelligence. This paper presents a versatile study on the neuromorphic implementation of learning. In particular, the paper aims at reviewing architectures intended for Learning and adaptation that advances neuromorphic design more towards human like intelligence. The various abstraction levels for implementing learning is the main contribution of the paper. Methods, issues and challenges in and at every level is analyzed. We have identified research gaps in modelling brain on hardware and motivations behind the current study of Neuromorphic chips are outlined.

Index Terms— Cognitive Sciences, Learning and Adaptation, Machine learning, Neuroscience, Neuromorphic Engineering, Synaptic Plasticity.

I. INTRODUCTION

BRAIN has always amazed us by its complex nature, though reliable and robust for many cognitive and metacognitive functions with a minimum amount of power consumption on the order of 25W [1, 2]. Scientists are putting all their brain to understanding the mysterious ways of information processing in the 1.5Kg wetware [3, 4]. Human brain is the subject matter due to its evolved neocortex as compared to other species [2]. One straight forward method to understand brain functionality is to create one.

There has been many Bio-inspired approaches to imitate human cognition [5], but that uses existing engineering products to mimic some of the behaviors of biological systems. There lies a huge gap between existing computing systems and their biological counterparts.

There are about 100 billion neurons in an adult human brain [6-8] weighing about 2% of total weight which are responsible for distributed and parallel computation. This analogous machine has dedicated point to point connections. Brain exhibits pattern classification, image recognition, motor control, learning, adaptation etc., whose performance cannot be matched with modern day super computers. Neuroscientist are of opinion that the difference in architecture is the main reason. To imitate human behavior and cognition we need to build computing devices whose architecture is not based on Von Neumann architecture but rather based on human nervous system.

Neuromorphic engineers take the lessons from biology and intend to reproduce into custom silicon VLSI (very large scale integration) chips. Neuromorphic Engineering aims at morphing neuroanatomy and neurophysiology into circuits which would not only depict human behavior with accuracy but also with efficiency [9].

Neuromorphic engineering attracted many researchers from various domain since its inception by Carver Mead in 1980s [10-13]. Inspired by the idea of hardware implementation of brain, Scientists from diverse group came under a single umbrella and started exploring neuro-biology and exploiting state-of-the art of Microelectronics Engineering.

In pursuit of understanding how the neurons, networks, systems and architectures collaborate and give rise to complex behaviors and cognitive aspects, neuromorphic engineering arises as an interdisciplinary domain. it takes lessons from biology (on neuroscience, brain structure, network interconnection, synaptic activity, information processing etc.), kinesiology (physiological, mechanical, and psychological mechanisms), Psychology (understanding behaviour,)physics (on semiconductor physics, sensors, potentials, voltages, diffusion in channel between source and drain etc.) chemistry (on ion-exchange, information exchange, coding etc.) cognition (learning, perception, attention, recognition) mathematics (on computations, complex algorithms etc.) computers (on parallel processing, decision making, artificial intelligence etc.), electronics engineering (on hardware implementation using transistor, circuits for dendrites, soma, neuron, cell, system and architectures, ICs and chips, Memristors, AERs, FPGAs, FPAAs, VLSI etc.).

Neuromorphic engineering also takes inspiration from interdisciplinary domains such as computational science, Cognitive neuroscience, Autonomous systems, Hybrid Intelligent systems etc.

Section II describes the Brain Anatomy, where selected structures and functions are abstracted. Section III explains various modelling approaches used to model a neuron as a whole and also parts such as dendrites, synapses, membrane potentials. Section IV describes various architectures and chips being proposed and implemented with a focus on implementation of Learning. Section V outlines the various issues in implementing Learning and Adaptation in VLSI Chips. Memory modelling is being discussed along with learning. In section VI we summarize the levels of implementation, approaches at every level, services provided and expected by every layer for hardware realization of Learning and Adaptation. At last paper concludes with open research issues and future work.

II. BRAIN MODEL ABSTRACTION

A. Placement and Arrangement

Brain is always placed (placement) very near to primary sensory organs which are used to see, smell, taste and hear. A typical operating frequency of neurons is around 100Hz as in [14], which is much smaller when compared to current speed of super computers. In spite of this brain processing outsmarts any existing computing device till date. For example: Visual perception is considered to happen in 200msec [15] and if every neuron is considered to have an individual delay of 10msec, then it would have taken less than 20 processing steps. This shows the (arrangement) massive point to point connectivity of neurons. This also challenges our existing parallel processing schemes [16].

B. Learning and Adaptation

Body adapts through exercise and brain adapts by learning [17]. The most astonishing function of brain is its ability to learn and adapt to the existing environment. Learning is output of both passive experiences and active search for knowledge. Learning is an Emergent phenomena [18]. Learning includes unlearning [19] the previous things, updating the previous conclusions and abstractions, understanding the best suitable decision i.e. Reinforcement Learning [20].

Marvin Minsky in his book [21] said “The principal activities of brains are making changes in themselves”. Learning happens by the virtue of plasticity of brain. Gopnick in his book [22] explains that Neural Network is like a telephone network, neurons transmit signals to target cells over long distances [23]. For instance the information sensed from eye is routed to primary visual area in occipital lobe. All these information processing happens through synapses which grow from 2500 synapses/neuron to 15000 synapses/neuron from birth to early childhood, which sums to 100 trillion synapse in a brain [24].

Learning takes place at synapses, the junction between neurons. When a new information is perceived it will be stored in short term memory which depends on chemical [25] (ion exchange) and electrical (spikes) events in brain [26-28]. As time precedes the information will be moved to long term memory which is accomplished by structural changes such as formation of new synapses [29].

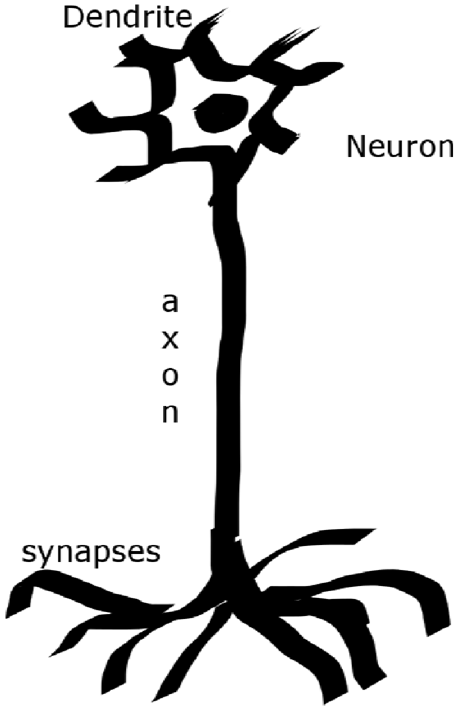

Fig. 1. Neuron is the basic component of human nervous system. Which has dendrites (receivers), axon (transmission line) and synapse (transmitters). Whenever a new learning happens there is change in synaptic activity due to which membrane potential changes and ion exchange happens. The connection will be for a long time if the learning results in Long term memory. This is abstraction of a neuron with a focus for learning and memory modelling.

C. Neuroscience and Abstraction levels

The fundamental step in designing Neuromorphic hardware is to choose the proper level of abstraction. The abstractions extracted from neuroscience about learning at the level of Neuron is explained here starting from Ion exchange to behaviour.

1) Ion Membrane Channel Abstraction:

The Action potentials (nerve impulses) also known as “spikes” are short duration events used for cell to cell communication [30] which lasts than a thousandth of a sec [31] and travel with a speed of 120 m/sec [32]. In the short duration the electrical membrane potential suddenly rises to a peak and immediately falls due to opening and closing of sodium ion channels followed by opening and closing of potassium ion channels [33-35].

Any resting neuron when triggered will become a spiking neuron as described in [36, 37]. The trigger for sensory organs can be corresponding stimuli [38, 39], obtained from a presynaptic axon which emits neurotransmitters in synaptic cleft which in turn bind to receptors (NMDA and non-NMDA receptors) of the postsynaptic neuron. Excitatory potential or inhibitory potential arises when the binding between two neurons opens ion channels and increases or decreases the ionic permeabilities of membrane and its potential respectively. Electrical synapses in [40, 41] may also result in transmission of action potential from one neuron to another by the virtue of gap potential and without any aid of chemicals as in [42, 43].

2) Synapse Abstraction:

The space between two neurons which includes presynaptic membrane, post synaptic membrane and synaptic cleft is called as synapse. Synapse plays an important role in information processing [23, 44, 45]. Learning and memory are associated with changes in synaptic connections between neurons [46, 47], which was evident by long term potentiation. Synaptic connections weakens over time and strengthens if activity is more, this reconfiguration of synaptic connections is termed as synaptic plasticity [48]. According to Hebbian theory, synaptic plasticity is one of the neurochemical foundations of memory and learning. Synaptic plasticity has many lessons about learning and memory [49, 50]. Adaptation in connections is postulated as learning and interconnected network of synapses are postulated to represent memory [51]. According to Hebbian learning theory “Cells that fire together, Wire together”, here together means which stimulate one another i.e. one cell has to fire and then the connected one will fire after a temporal time delay, hence termed as spike-timing-dependent plasticity [52]. When cells fire in sync, long lasting changes of synaptic efficacies were found [53, 54] they create Long Term Potentiation (LTP) occurs which help us to remember whereas if the firing is out of sync then Long Term Depression (LTD) occurs which helps to forget [55-57].

The synaptic abstraction considers the phenomenological models which are based on simple I/O relationship between neuronal activity and synaptic plasticity, which accounts for higher level phenomena such as memory and development of neuronal selectivity [58].

3) Single Neuron Abstraction:

Neurons are the electrically excitable brain cells which transmit information by electrochemical signaling [59]. Neurons vary from 0.4 microns to 0.1mm in diameter and from fraction of inch to several feet [60] in length. There are about 10000 types of neurons but based on functionality, neurons can be classified as sensory neurons which convey information from sensory organs to central nervous systems, motor neurons which transmit information from central nervous system to effector cells and interneurons which interconnect neurons [61]. The basic information processing unit in brain is neuron. Neurons process all the information flowing within, in and out of Central nervous system [62]. It processes the information we receive from sensory tissues/organs, all the motor information and all the cognitive information through which we are capable of reasoning and thinking.

Glia cells are also nerve cells which forms 90% of brain. They are not involved in signaling but responsible for maintenance of neurons, by creating myelin [63] and by providing mechanical and nutritional support [64-66] and all housekeeping work of neurons. Types of glial cells include Schwann's Cells, Satellite Cells, Microglia, Oligodendroglia, and Astroglia [67].

4) Neural Network abstraction:

An average human brain contains around 100 billion neurons [68]. If every neuron is assumed to have 10000 synaptic connections then our brain is a computer made of a processor which processes at least 1 trillion bit per sec [69, 70], and the memory ranges from 1 to 1000 terabytes [71]. Obviously all neurons don't network in a same fashion as there are many diverse functionality to be achieved. Neural networks can be best studied in considering one system at a time.

In vision system there are a series of events. Light falls on an object, gets reflected and travels through cornea, passes through lens which focuses light on retina (sensory tissue), where rods detect light and cones detect color. Rods and cones are transducers which convert light rays into electrical impulses and pass it to brain through optic nerve we then "see" what we are looking it [72]. Retina is the functional sensory receptor of eye, which contains 3 layers of interconnected neurons: rods and cones form the first layer which is then connected to interneurons (forms second layer) which relays the signals to ganglion cells (forms the third layer). The axons of ganglion cells form optic nerve.

In auditory system, the sound waves perceived by outer ear are modulated by middle ear and transmitted to cochlear nerve by inner ear. The inner ear receives vibrations from middle and outer ear, convert them into nerve impulse. Within the inner ear is cochlea which acts as functional sensory receptor of ear. Ear is also involved in providing balance to body in both moving and stationary condition.

5) Brain system Abstraction:

Human brain is largely divided in to 3 parts: cerebrum, cerebellum and brain stem. Brain stem controls respiration digestion heartrate etc., as in [73-75]. Cerebellum known as little brain [76], is responsible for motor control and also involved in cognitive functions such as attention, language, fear regulation, pain and pleasure [77-83]. Cerebrum is the superior most part in central nervous system [84, 85], is responsible for all voluntary actions.

Cerebrum is divided into right and left hemisphere (which controls signal processing of left part and right part of the body respectively) by a longitudinal fissure [86, 87]. The cerebrum has cortex and subcortical structures such as hippocampus, basal ganglia and olfactory bulb which are intended for information consolidation from short term memory to long term memory [88-91], decision making [92-94] and smell [95-97] respectively. Cortex communicate with subcortical structures via thalamus

[98-101]. Thalamus mediate all sensory information perceived from subcortical structures to neocortex except olfactory system [102].

Cortex is highly interconnected and about 99% connections are between different areas of cortex [103] only 1% is dedicated for communication with subcortical parts. Cortex is comprised of three parts: sensory, motor and association areas [104]. The sensory information received from sense organs are processed in sensory areas such as Visual cortex, auditory cortex and somatosensory cortex which takes care of vision, audition and touch [105, 106]. Association areas play a vital role in planning, actions and abstract thinking. The organization or networking of association areas is highly debated [107, 108].

Cerebral cortex is divided into four sections [109] called lobes, frontal lobe (contains dopamine-sensitive neurons and involved in conscious thought and higher mental functions such as reward, attention, decision making, reasoning, planning, processing short term memory and retaining long term memory), parietal lobe (involved in integrating sensory information, spatial sense, navigation, recognition, perception of stimuli), temporal lobe (involved in processing sensory information into meaningful abstractions for retention of visual memories, speech, emotional association and plays a vital role in long term memory) and occipital lobe (visual processing). The media temporal lobe present inside temporal lobe is involved in declarative and episodic memory [110].

Hippocampus is only region which can grow new neurons [111]. Long term potentiation – one of the mechanism responsible for memory was first discovered in hippocampus [47, 112, 113]. It is responsible for spatial memory and navigation. Due to the densely packed neural layers, hippocampus generate largest EEG signals by brain. These waves not only modulate the spikes of hippocampal neurons but also synchronize [114]. The EEG pattern is called theta rhythm [115]. Many theories suggest that the theta rhythm has effects on learning and memory [116]. Basal ganglia (especially striatum) is responsible for formation and retrieval of procedural memory [117].

6) Behavioral abstraction:

If a group of neurons (cell assemblies) are constantly simulating each other to maintain activity, so as to create a temporal representation of current task, then it is termed as working memory [118]. If new long lasting connections are created, so as to remember a specific event, then it is termed as episodic memory in [119], this is where hippocampus comes into picture. To learn and remember ideas, concepts and things which cannot be drawn from personnel experience (such as sounds of letters) there need to be changes in connections between some cells which represent specific types of information as explained in [120]. This is termed as semantic memory where cerebral cortex come into picture. Centered around basal ganglia a network of brain areas implement reward and punishment based learning called instrumental learning [121]. Motor learning involves micro adjustments of parameters of movements for which basal ganglia and cerebellum are included [122].

III. IMPLEMENTATION LEVELS OF BRAIN MODELS

Modelling is a reductionist approach. Models reduce complexity and provide simplified representation of real systems. All neuronal dynamics is not yet understood, hence creating an exact replica is not under our grasp. Abstraction is done at every level to make our life simple.

Brain being the most complex system, its implementation can be studied in a hierarchy. The interactions of different neuronal components give rise to behaviour. Since behaviour is a collective function of different neural components, its abstraction is placed above system level.

Protein/Genetic level describes the genes structure. It's a neglected/not yet explored field in Neuromorphic Engineering.

At Membrane Level, electrical and ion exchange happens. Transistor is often abstracted as switch: ON or OFF. But the V-I characteristics shows that current flowing is smooth and steep function of applied Voltage. Transistors work in subthreshold region where the V-I characteristics resemble the current voltage relationships in molecular structures on surface of brain cells. Hence membrane level abstractions and implementations are done at transistor level.

Intra-neuron communication happens through synapses. Synaptic plasticity is the reason for the emergent animal behaviors: adaptation and Learning. In recent years the learning process has dragged more attention. Selective attention is the main functionality of this abstraction level.

The synaptic plasticity can be implemented using CMOS circuits. Memristors are an alternative, which also has answers to memory modelling. Large scale memristive fabric is yet to be realized. Selective attention, Efficient learning and memory modelling is the biggest open research issue at synaptic level.

Perceptron's implementation in 1950's was the pioneering work, which was foundation for implementation of Artificial Neural Networks on hardware. Perceptron is computational model of Neuron. Hodgkin-Huxley and Morris-Lecar [123, 124] models are conductance based which has high biological precision but comes with huge cost. Another type (Type II) are spike based such as Integrate and fire model which describe temporal behaviour of spikes which are earliest and simplest models [37].

Spikes are used in nervous system for information transmission. Intra neuron Communication is important aspect at system level. Address event representation protocol proposed in 1991 to mimic information coding of brain. AER assigns a fixed address to every neuron, by using which neurons continuously update their central system about their excitation levels. This updated info is sent to upper/higher layers. AER is a communication protocol for spiking neurons between different layers [125-128].This field has attracted a huge community of researchers who are engineering various protocols for inter and intra chip communication. AER scheme resembles to the Internet Protocol (IP) addressing in computer networking where information is routed to individual host corresponding to the IP address.

Selecting the appropriate level of abstraction is very important [129]. We have choice of Top-down approach, where we arrive to the neuron model keeping behaviour in our mind. Here we intend to reflect all biological components due to which it may be expensive, and the models become too complex. In Bottom-up approach we generalize one model of neuron and climb up to behavior level where most of the time the models fail to replicate the biological counterpart. This ambiguity whether to choose top down approach (complex biological implementation, Biology has the upper hand) or Bottom-up approach (abstract level implementations, existing engineering technology has the upper hand) leads us to the Valley of Death.

TABLE I. **LEVELS OF IMPLEMENTATION**

levels	**Neuromorphic Correspondence for Implementation Hierarchy**		
	Hierarchy	***Neuroscience***	***Electrical science***
7	Behavior Level	Mind	Architecture
6	System Level	Brain system	Macro Block
5	Circuit Level	Local Neuronal population	Block/Cell
4	Component Level	Single Neuron	Perceptron
3	Device Level	Synapses	CMOS/ Memristors
2	Membrrane Level	Channel Ions	Transistor
1	Protein/ Genetic	Genes	------

The 2 approaches are in fact 2 faces of same coin, no matter which approach we inculcate, the million dollar question is : “Is the machine Intelligent ?” finding the right trade off and compromises to make it more real (to humans) and realizable is the open research issue.

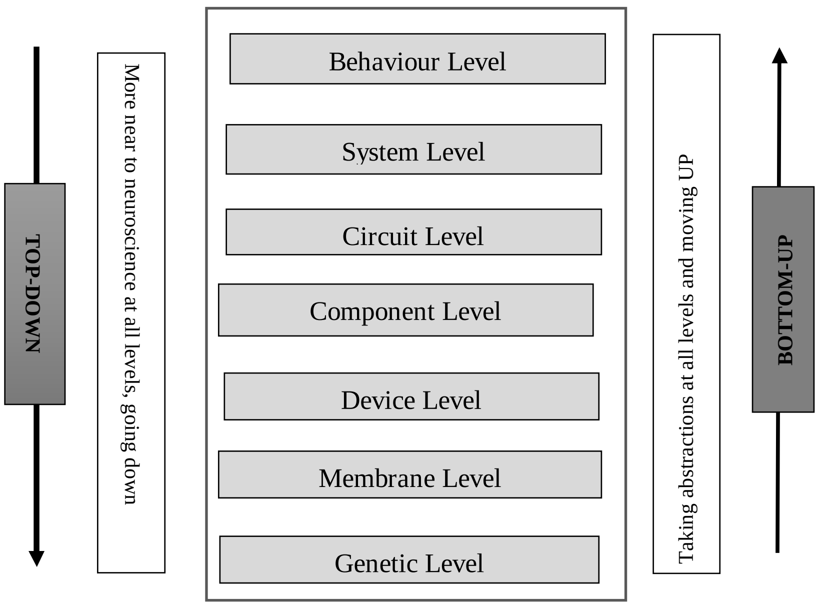

Fig. 2. Implementation Approaches

IV. CONCLUSION

This paper has done a brief review of various tradeoffs to be considered during Hardware implementation of Bio-inspired Computing Architectures. Levels of Implementation is an important contribution of this paper. Implementation approaches provide a clear idea for a researcher to start at what level and what to expect from the upper layer and what services are necessary to the lower layer. This paper brings out many open research issues pertaining to morphed circuits. Some milestones achieved are mentioned, and the things yet to be achieved are discussed. This has also discussed the gap between the software simulation results and Hardware emulation results.

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REFERENCES

[1] Y. Q. Zhang, M. D. Fraser, R. A. Gagliano, and A. Kandel, "Granular neural networks for numerical-linguistic data fusion and knowledge discovery," *IEEE Trans Neural Netw,* vol. 11, pp. 658-67, 2000.

[2] J. H. Lui, D. V. Hansen, and A. R. Kriegstein, "Development and evolution of the human neocortex," *Cell,* vol. 146, pp. 18-36, Jul 8 2011.

[3] W. Spann and H. O. Dustmann, "[Weight of the human brain and its dependence on age, body length, cause of death and occupation]," *Dtsch Z Gesamte Gerichtl Med,* vol. 56, pp. 299-317, 1965.

[4] T. W. Jenkins and R. C. Truex, "Dissection of the Human Brain as a Method for Its Fractionation by Weight," *Anat Rec,* vol. 147, pp. 359-66, Nov 1963.

[5] B. Fasel, "An introduction to bio-inspired artificial neural network architectures," *Acta Neurol Belg,* vol. 103, pp. 6-12, Mar 2003.

[6] R. Lent, F. A. Azevedo, C. H. Andrade-Moraes, and A. V. Pinto, "How many neurons do you have? Some dogmas of quantitative neuroscience under revision," *Eur J Neurosci,* vol. 35, pp. 1-9, Jan 2012.

[7] S. Herculano-Houzel, "The human brain in numbers: a linearly scaled-up primate brain," *Front Hum Neurosci,* vol. 3, p. 31, 2009.

[8] F. A. Azevedo, L. R. Carvalho, L. T. Grinberg, J. M. Farfel, R. E. Ferretti, R. E. Leite, *et al.*, "Equal numbers of neuronal and nonneuronal cells make the human brain an isometrically scaled-up primate brain," *J Comp Neurol,* vol. 513, pp. 532-41, Apr 10 2009.

[9] J. Arthur and K. Boahen, "Learning in silicon: timing is everything," *Advances in neural information processing systems,* vol. 18, p. 75, 2006.

[10] C. Mead and L. Conway, *Introduction to VLSI systems*. Reading, Mass.: Addison-Wesley, 1980.

[11] C. Mead, *Analog VLSI and neural systems*. Reading, Mass.: Addison-Wesley, 1989.

[12] C. Mead and M. Ismail, *Analog VLSI implementation of neural systems*. Boston: Kluwer Academic Publishers, 1989.

[13] C. Mead, "Neuromorphic electronic systems," *Proceedings of the IEEE,* vol. 78, pp. 1629-1636, 1990.

[14] G. E. Perlin, A. M. Sodagar, and K. D. Wise, "A neural amplifier with high programmable gain and tunable bandwidth," *Conf Proc IEEE Eng Med Biol Soc*, vol. 2008, pp. 3154-7, 2008.

[15] S. J. Thorpe and M. Imbert, "Biological constraints on connectionist modelling," *Connectionism in perspective,* pp. 63-92, 1989.

[16] B. R. Rau and J. A. Fisher, "Instruction-level parallel processing: history, overview, and perspective," *The journal of Supercomputing,* vol. 7, pp. 9-50, 1993.

[17] S. J. Blakemore and U. Frith, "The learning brain: lessons for education: a précis," *Developmental science,* vol. 8, pp. 459-465, 2005.

[18] W. Stroup and U. Wilensky, "Assessing learning as emergent phenomena: Moving constructivist statistics beyond the bell curve," *Handbook of methods for research in learning and teaching science and mathematics,* pp. 877-911, 2000.

[19] J. J. Hopfield, D. Feinstein, and R. Palmer, "'Unlearning'has a stabilizing effect in collective memories," 1983.

[20] R. J. Williams, *Reinforcement learning in connectionist networks: A mathematical analysis*: University of California, San Diego, 1986.

[21] M. Minsky, *Society of mind*: Simon and Schuster, 1988.

[22] A. Gopnik, A. N. Meltzoff, and P. K. Kuhl, *The scientist in the crib: Minds, brains, and how children learn*: William Morrow & Co, 1999.

[23] E. R. Kandel, J. H. Schwartz, and T. M. Jessell, *Principles of neural science* vol. 4: McGraw-Hill New York, 2000.

[24] R. W. Williams and K. Herrup, "The control of neuron number," *Annu Rev Neurosci,* vol. 11, pp. 423-53, 1988.

[25] R. S. Zucker, "Short-term synaptic plasticity," *Annual review of neuroscience,* vol. 12, pp. 13-31, 1989.

[26] D. S. Jeong, I. Kim, M. Ziegler, and H. Kohlstedt, "Towards artificial neurons and synapses: a materials point of view," *RSC Advances,* vol. 3, pp. 3169-3183, 2013.

[27] H.-Y. Zhang and K. T. Sillar, "Short-term memory of motor network performance via activity-dependent potentiation of Na+/K+ pump function," *Current Biology,* vol. 22, pp. 526-531, 2012.

[28] J. J. Hopfield, *Brain, neural networks, and computation*: Springer, 1999.

[29] G. J. Tortora and S. Grabowski, "Principles of anatomy and physiology, 1996," *Biological Sciences Textbook Inc., ISBN 0-673-99354-X.*

[30] W. A. Rushton, "The structure responsible for action potential spikes in the cat's retina," *Nature,* vol. 164, p. 743, Oct 29 1949.

[31] W. R. Amberson, A. Parpart, and G. Sanders, "An analysis of the low-voltage elements of the action-potential wave in nerve," *American Journal of Physiology--Legacy Content,* vol. 97, pp. 154-179, 1931.

[32] A. I. Undrovinas, V. F. Pastushenko, and V. S. Markin, "[Calculation of the shape and speed of nerve impulses]," *Dokl Akad Nauk SSSR,* vol. 204, pp. 229-32, May-Jun 1972.

[33] L. Cohen, "Changes in neuron structure during action potential propagation and synaptic transmission," *Physiological Reviews,* vol. 53, pp. 373-418, 1973.

[34] C. M. Armstrong and F. Bezanilla, "Charge movement associated with the opening and closing of the activation gates of the Na channels," *The Journal of General Physiology,* vol. 63, pp. 533-552, 1974.

[35] G. Romey, J. Abita, H. Schweitz, and G. Wunderer, "Sea anemone toxin: a tool to study molecular mechanisms of nerve conduction and excitation-secretion coupling," *Proceedings of the National Academy of Sciences,* vol. 73, pp. 4055-4059, 1976.

[36] Y. D. Sato and M. Shiino, "Spiking neuron models with excitatory or inhibitory synaptic couplings and synchronization phenomena," *Phys Rev E Stat Nonlin Soft Matter Phys,* vol. 66, p. 041903, Oct 2002.

[37] E. M. Izhikevich, "Simple model of spiking neurons," *IEEE Trans Neural Netw,* vol. 14, pp. 1569-72, 2003.

[38] W. Gerstner and W. M. Kistler, *Spiking neuron models: Single neurons, populations, plasticity*: Cambridge university press, 2002.

[39] R. Kempter, W. Gerstner, and J. L. Van Hemmen, "Hebbian learning and spiking neurons," *Physical Review E,* vol. 59, p. 4498, 1999.

[40] T. H. Bullock, R. Orkand, and A. Grinnell, "Introduction to nervous systems," 1977.

[41] K. Schmidt-Nielsen, *Animal physiology: adaptation and environment*: Cambridge University Press, 1997.

[42] G. Fried, "Synaptic vesicles and release of transmitters: new insights at the molecular level," *Acta Physiol Scand,* vol. 154, pp. 1-15, May 1995.

[43] G. Clarke and L. P. Merrick, "A tentative identification of the synaptic transmitters involved in the neural regulation of oxytocin release [proceedings]," *J Physiol,* vol. 277, pp. 19P-20P, Apr 1978.

[44] P. H. Lindsay and D. A. Norman, *Human information processing: An introduction to psychology*: Academic Press, 2013.

[45] C. Koch and I. Segev, "The role of single neurons in information processing," *nature neuroscience,* vol. 3, pp. 1171-1177, 2000.

[46] S. R. Y. Cajal, "The Croonian Lecture: La fine structure des centres nerveux," *Proceedings of the Royal Society of London,* vol. 55, pp. 444-468, 1894.

[47] T. Lomo, "The discovery of long-term potentiation," *Philos Trans R Soc Lond B Biol Sci,* vol. 358, pp. 617-20, Apr 29 2003.

[48] W. C. Abraham and M. F. Bear, "Metaplasticity: the plasticity of synaptic plasticity," *Trends in neurosciences,* vol. 19, pp. 126-130, 1996.

[49] S. Maren and M. Baudry, "Properties and mechanisms of long-term synaptic plasticity in the mammalian brain: relationships to learning and memory," *Neurobiology of learning and memory,* vol. 63, pp. 1-18, 1995.

[50] S. Martin, P. Grimwood, and R. Morris, "Synaptic plasticity and memory: an evaluation of the hypothesis," *Annual review of neuroscience,* vol. 23, pp. 649-711, 2000.

[51] D. Hebb, "0.(1949). The organisation of behaviour," *New York*.

[52] N. Caporale and Y. Dan, "Spike timing-dependent plasticity: a Hebbian learning rule," *Annu Rev Neurosci,* vol. 31, pp. 25-46, 2008.

[53] T. V. Bliss and T. Lømo, "Long-lasting potentiation of synaptic transmission in the dentate area of the anaesthetized rabbit following stimulation of the perforant path," *The Journal of physiology,* vol. 232, pp. 331-356, 1973.

[54] T. V. Bliss and A. Gardner-Medwin, "Long-lasting potentiation of synaptic transmission in the dentate area of the unanaesthetized rabbit following stimulation of the perforant path," *The Journal of physiology,* vol. 232, pp. 357-374, 1973.

[55] S. A. Siegelbaum and E. R. Kandel, "Learning-related synaptic plasticity: LTP and LTD," *Current opinion in neurobiology,* vol. 1, pp. 113-120, 1991.

[56] T. Sejnowski, "Statistical constraints on synaptic plasticity," *Journal of theoretical biology,* vol. 69, pp. 385-389, 1977.

[57] G. S. Stent, "A physiological mechanism for Hebb's postulate of learning," *Proceedings of the National Academy of Sciences,* vol. 70, pp. 997-1001, 1973.

[58] A. Morrison, M. Diesmann, and W. Gerstner, "Phenomenological models of synaptic plasticity based on spike timing," *Biological cybernetics,* vol. 98, pp. 459-478, 2008.

[59] P. S. Churchland, *Neurophilosophy: Toward a unified science of the mind-brain*: MIT press, 1989.

[60] M. P. Muehlenbein, *Human evolutionary biology*: Cambridge University Press, 2010.

[61] B. Kolb and I. Q. Whishaw, *An introduction to brain and behavior*: Worth Publishers, 2001.

[62] R. Stufflebeam, "Neurons, synapses, action potentials, and neurotransmission," *Consortium on Cognitive Science Instruction,* 2008.

[63] R. P. Bunge, "Glial cells and the central myelin sheath," *Physiological Reviews,* vol. 48, pp. 197-251, 1968.

[64] P. G. Haydon, "GLIA: listening and talking to the synapse," *Nature Reviews Neuroscience,* vol. 2, pp. 185-193, 2001.

[65] J. S. Bains and S. H. Oliet, "Glia: they make your memories stick!," *Trends in neurosciences,* vol. 30, pp. 417-424, 2007.

[66] R. Galambos, "A glia-neural theory of brain function," *Proceedings of the National Academy of Sciences of the United States of America,* vol. 47, p. 129, 1961.

[67] K. R. Jessen, "Glial cells," *The international journal of biochemistry & cell biology,* vol. 36, pp. 1861-1867, 2004.

[68] H. Creasey and S. I. Rapoport, "The aging human brain," *Annals of neurology,* vol. 17, pp. 2-10, 1985.

[69] H. De Garis, *CAM-BRAIN the evolutionary engineering of a billion neuron artificial brain by 2001 which grows/evolves at electronic speeds inside a cellular automata machine (CAM)*: Springer, 1996.

[70] J. T. Schwartz, "The new connectionism: Developing relationships between neuroscience and artificial intelligence," *Daedalus,* pp. 123-141, 1988.

[71] H. Moravec, "When will computer hardware match the human brain," *Journal of evolution and technology,* vol. 1, p. 10, 1998.

[72] D. A. Atchison, G. Smith, and G. Smith, "Optics of the human eye," 2000.

[73] S. B. Mazzone and B. J. Canning, "Central nervous system control of the airways: pharmacological implications," *Curr Opin Pharmacol,* vol. 2, pp. 220-8, Jun 2002.

[74] J. H. Jiao, P. G. Guyenet, and A. J. Baertschi, "Lower brain stem controls cardiac ANF secretion," *Am J Physiol,* vol. 263, pp. H198-207, Jul 1992.

[75] C. G. Summers and J. C. Parker, Jr., "The brain stem in sudden infant death syndrome. A postmortem survey," *Am J Forensic Med Pathol,* vol. 2, pp. 121-7, Jun 1981.

[76] T. Butts, M. J. Green, and R. J. Wingate, "Development of the cerebellum: simple steps to make a 'little brain'," *Development,* vol. 141, pp. 4031-41, Nov 2014.

[77] H. J. De Smet, P. Paquier, J. Verhoeven, and P. Marien, "The cerebellum: its role in language and related cognitive and affective functions," *Brain Lang,* vol. 127, pp. 334-42, Dec 2013.

[78] M. Dzon, "[Cerebellum--its role in development of cognitive and aging functions]," *Ann Acad Med Stetin,* pp. 105-10, 2013.

[79] N. H. Barmack and V. Yakhnitsa, "Functions of interneurons in mouse cerebellum," *J Neurosci,* vol. 28, pp. 1140-52, Jan 30 2008.

[80] L. A. Kalashnikova, "[The role of the cerebellum in the organization of higher mental functions]," *Zh Nevrol Psikhiatr Im S S Korsakova,* vol. 101, pp. 55-60, 2001.

[81] M. Gomez-Beldarrain and J. C. Garcia-Monco, "[Cerebellum and cognitive functions]," *Rev Neurol,* vol. 30, pp. 1274-5, Jun 16-30 2000.

[82] H. C. Leiner, A. L. Leiner, and R. S. Dow, "Cognitive and language functions of the human cerebellum," *Trends Neurosci,* vol. 16, pp. 444-7, Nov 1993.

[83] I. Daum, H. Ackermann, M. M. Schugens, C. Reimold, J. Dichgans, and N. Birbaumer, "The cerebellum and cognitive functions in humans," *Behav Neurosci,* vol. 107, pp. 411-9, Jun 1993.

[84] N. Tzourio, F. E. Massioui, F. Crivello, M. Joliot, B. Renault, and B. Mazoyer, "Functional anatomy of human auditory attention studied with PET," *Neuroimage,* vol. 5, pp. 63-77, Jan 1997.

[85] T. A. Blaxton, S. Y. Bookheimer, T. A. Zeffiro, C. M. Figlozzi, W. D. Gaillard, and W. H. Theodore, "Functional mapping of human memory using PET: comparisons of conceptual and perceptual tasks," *Can J Exp Psychol,* vol. 50, pp. 42-56, Mar 1996.

[86] J. Sergent, "A new look at the human split brain," *Brain,* vol. 110 (Pt 5), pp. 1375-92, Oct 1987.

[87] Turner, "A Human Cerebrum Imperfectly Divided into two Hemispheres," *J Anat Physiol,* vol. 12, pp. 241-53, Jan 1878.

[88] C. James, S. Morand, S. Barcellona-Lehmann, C. M. Michel, and A. Schnider, "Neural transition from short- to long-term memory and the medial temporal lobe: a human evoked-potential study," *Hippocampus,* vol. 19, pp. 371-8, Apr 2009.

[89] R. P. Vertes, "Hippocampal theta rhythm: a tag for short-term memory," *Hippocampus,* vol. 15, pp. 923-35, 2005.

[90] R. P. Kesner and R. O. Hopkins, "Short-term memory for duration and distance in humans: role of the hippocampus," *Neuropsychology,* vol. 15, pp. 58-68, Jan 2001.

[91] M. Salcman, "A hypothesis concerning the structural relationship between memory and emotion," *Med Hypotheses,* vol. 4, pp. 581-90, Nov-Dec 1978.

[92] P. P. Balasubramani, V. S. Chakravarthy, B. Ravindran, and A. A. Moustafa, "An extended reinforcement learning model of basal ganglia to understand the contributions of serotonin and dopamine in risk-based decision making, reward prediction, and punishment learning," *Front Comput Neurosci,* vol. 8, p. 47, 2014.

[93] J. J. Cheng and W. S. Anderson, "The role of the basal ganglia in decision making: a new fMRI study," *Neurosurgery,* vol. 71, pp. N14-5, Oct 2012.

[94] O. Hikosaka, "[Decision-making and learning by cortico-basal ganglia network]," *Brain Nerve,* vol. 60, pp. 799-813, Jul 2008.

[95] F. Zhao, M. A. Holahan, A. K. Houghton, R. Hargreaves, J. L. Evelhoch, C. T. Winkelmann, *et al.*, "Functional imaging of olfaction by CBV fMRI in monkeys: Insight into the role of olfactory bulb in habituation," *Neuroimage,* vol. 106, pp. 364-72, Feb 1 2015.

[96] O. Hendin, D. Horn, and M. V. Tsodyks, "The role of inhibition in an associative memory model of the olfactory bulb," *J Comput Neurosci,* vol. 4, pp. 173-82, Apr 1997.

[97] R. M. Sullivan, D. R. Zyzak, P. Skierkowski, and D. A. Wilson, "The role of olfactory bulb norepinephrine in early olfactory learning," *Brain Res Dev Brain Res,* vol. 70, pp. 279-82, Dec 18 1992.

[98] V. Kumari, D. Fannon, E. R. Peters, D. H. Ffytche, A. L. Sumich, P. Premkumar, *et al.*, "Neural changes following cognitive behaviour therapy for psychosis: a longitudinal study," *Brain,* vol. 134, pp. 2396-407, Aug 2011.

[99] B. W. Connors and M. A. Long, "Electrical synapses in the mammalian brain," *Annu Rev Neurosci,* vol. 27, pp. 393-418, 2004.

[100] M. A. Long, C. E. Landisman, and B. W. Connors, "Small clusters of electrically coupled neurons generate synchronous rhythms in the thalamic reticular nucleus," *J Neurosci,* vol. 24, pp. 341-9, Jan 14 2004.

[101] B. Libet, D. K. Pearl, D. E. Morledge, C. A. Gleason, Y. Hosobuchi, and N. M. Barbaro, "Control of the transition from sensory detection to sensory awareness in man by the duration of a thalamic stimulus. The cerebral 'time-on' factor," *Brain,* vol. 114 (Pt 4), pp. 1731-57, Aug 1991.

[102] R. L. Isaacson, *Limbic system*: Wiley Online Library, 1982.

[103] V. Braitenberg and A. Schüz, *Anatomy of the cortex: Statistics and geometry*: Springer-Verlag Publishing, 1991.

[104] M. W. Miller and B. A. Vogt, "Direct connections of rat visual cortex with sensory, motor, and association cortices," *Journal of Comparative Neurology,* vol. 226, pp. 184-202, 1984.

[105] C. Kayser, C. I. Petkov, M. Augath, and N. K. Logothetis, "Integration of touch and sound in auditory cortex," *Neuron,* vol. 48, pp. 373-384, 2005.

[106] W. Walter, "The convergence and interaction of visual, auditory, and tactile responses in human nonspecific cortex," *Annals of the New York Academy of Sciences,* vol. 112, pp. 320-361, 1964.

[107] B. T. Yeo, F. M. Krienen, J. Sepulcre, M. R. Sabuncu, D. Lashkari, M. Hollinshead, *et al.*, "The organization of the human cerebral cortex estimated by intrinsic functional connectivity," *Journal of neurophysiology,* vol. 106, pp. 1125-1165, 2011.

[108] R. K. Srivastava, J. Masci, F. Gomez, and J. Schmidhuber, "Understanding Locally Competitive Networks," *arXiv preprint arXiv:1410.1165,* 2014.

[109] P. E. Roland, *Brain activation*: Wiley-Liss, 1993.

[110] E. Tulving and H. J. Markowitsch, "Episodic and declarative memory: role of the hippocampus," *Hippocampus,* vol. 8, 1998.

[111] S. A. Bayer, "Neuron Production in the Hippocampus and Olfactory Bulb of the Adult Rat Brain: Addition or Replacement? a," *Annals of the New York Academy of Sciences,* vol. 457, pp. 163-172, 1985.

[112] M. R. Bennett, "The concept of long term potentiation of transmission at synapses," *Prog Neurobiol,* vol. 60, pp. 109-37, Feb 2000.

[113] J. G. Howland and Y. T. Wang, "Synaptic plasticity in learning and memory: stress effects in the hippocampus," *Prog Brain Res,* vol. 169, pp. 145-58, 2008.

[114] E. V. Lubenov and A. G. Siapas, "Hippocampal theta oscillations are travelling waves," *Nature,* vol. 459, pp. 534-539, 2009.

[115] G. Buzsáki, "Theta oscillations in the hippocampus," *Neuron,* vol. 33, pp. 325-340, 2002.

[116] G. Buzsaki, *Rhythms of the Brain*: Oxford University Press, 2006.

[117] C. Pittenger, S. Fasano, D. Mazzocchi-Jones, S. B. Dunnett, E. R. Kandel, and R. Brambilla, "Impaired bidirectional synaptic plasticity and procedural memory formation in striatum-specific cAMP response element-binding protein-deficient mice," *J Neurosci,* vol. 26, pp. 2808-13, Mar 8 2006.

[118] C. E. Curtis and M. D'Esposito, "Persistent activity in the prefrontal cortex during working memory," *Trends Cogn Sci,* vol. 7, pp. 415-423, Sep 2003.

[119] E. Tulving and H. J. Markowitsch, "Episodic and declarative memory: role of the hippocampus," *Hippocampus,* vol. 8, pp. 198-204, 1998.

[120] A. Martin and L. L. Chao, "Semantic memory and the brain: structure and processes," *Curr Opin Neurobiol,* vol. 11, pp. 194-201, Apr 2001.

[121] B. W. Balleine, M. Liljeholm, and S. B. Ostlund, "The integrative function of the basal ganglia in instrumental conditioning," *Behav Brain Res,* vol. 199, pp. 43-52, Apr 12 2009.

[122] K. Doya, "Complementary roles of basal ganglia and cerebellum in learning and motor control," *Curr Opin Neurobiol,* vol. 10, pp. 732-9, Dec 2000.

[123] A. L. Hodgkin and A. F. Huxley, "A quantitative description of membrane current and its application to conduction and excitation in nerve," *J Physiol,* vol. 117, pp. 500-44, Aug 1952.

[124] C. Morris and H. Lecar, "Voltage oscillations in the barnacle giant muscle fiber," *Biophys J,* vol. 35, pp. 193-213, Jul 1981.

[125] R. I. Davis and J. A. Ferraro, "Comparison between AER and behavioral thresholds in normally and abnormally hearing chinchillas," *Ear Hear,* vol. 5, pp. 153-9, May-Jun 1984.

[126] A. Linares-Barranco, G. Jimenez-Moreno, B. Linares-Barranco, and A. Civit-Balcells, "On algorithmic rate-coded AER generation," *IEEE Trans Neural Netw,* vol. 17, pp. 771-88, May 2006.

[127] C. Zamarreno-Ramos, T. Serrano-Gotarredona, and B. Linares-Barranco, "A 0.35 mum sub-ns wake-up time ON-OFF switchable LVDS driver-receiver chip I/O pad pair for rate-dependent power saving in AER bit-serial links," *IEEE Trans Biomed Circuits Syst,* vol. 6, pp. 486-97, Oct 2012.

[128] B. Zhao, R. Ding, S. Chen, B. Linares-Barranco, and H. Tang, "Feedforward Categorization on AER Motion Events Using Cortex-Like Features in a Spiking Neural Network," *IEEE Trans Neural Netw Learn Syst,* Oct 22 2014.

[129] J. V. Arthur and K. Boahen, "Silicon-Neuron Design: A Dynamical Systems Approach," *IEEE Trans Circuits Syst I Regul Pap,* vol. 58, pp. 1034-1043, 2011.