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A Marr's Three-Level Analytical Framework for Neuromorphic Electronic Systems

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Neuromorphic electronics, an emerging field that aims for building electronic mimics of the biological brain, holds promise for reshaping the frontiers of information technology and enabling a more intelligent and efficient computing paradigm. As their biological brain counterpart, the neuromorphic electronic systems are complex, having multiple levels of organization. Inspired by David Marr's famous three-level analytical framework developed for neuroscience, the advances in neuromorphic electronic systems are selectively surveyed and given significance to these research endeavors as appropriate from the computational level, algorithmic level, or implementation level. Under this framework, the problem of how to build a neuromorphic electronic system is defined in a tractable way. In conclusion, the development of neuromorphic electronic systems confronts a similar challenge to the one neuroscience confronts, that is, the limited constructability of the low-level knowledge (implementations and algorithms) to achieve high-level brain-like (human-level) computational functions. An opportunity arises from the communication among different levels and their codesign. Neuroscience lab-on-neuromorphic chip platforms offer additional opportunity for mutual benefit between the two disciplines.

1. Introduction

The human brain is a powerful natural information processing system that has evolved over millions of years. The earliest concept of the brain and the attention to its inner workings dated to the time of ancient civilization.[1] Modern neuroscience has revealed that the human brain contains roughly the same number of neurons as there are stars in the Milky Way galaxy and 1,000 times more synapses.[2] With such staggering complexity, it is no surprise that the details of the brain mechanisms are still largely unknown and the brain still remains a "black box" to be deciphered. In the past few decades, the research advances of neuroscience have shed new light on the "black box."[3]

Since roughly the same period of time of the earliest attempt to understand the brain,[1] there have already been many depictions of devices resembling animals and humans.[4] Although the key role of the brain in human intelligence might not have been recognized at that time, artificial brains have been the indispensable components of modern intelligent machines that can learn, adapt, interact with the environment, and perform human-like (or even human-level) tasks. The modern concept of such artificial intelligent system began to be developed with the onset of the Industrial Revolution, which allowed the use of complex mechanics. Later, electronics evolved into the driving force of its development.[4]

Hailed as the world's first electronic brain, Electronic Numerical Integrator and Computer (ENIAC) came online in

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1946 as a major step forwards in our ability to process information.[5] Since then, the comparison between computer and the human brain has never stopped. The computer has initially been used to replace the human brain to perform fixed rule-based computing tasks, faster, and more precisely.[6] However, it has gradually been realized that von Neumann style digital computers lag behind human brains in key areas, such as adaptivity, generalization, and fault tolerance. In addition, with the rise of data-intensive computing workloads due to the popularity of mobile devices and the internet, the "memory wall" problem that exists in von Neumann architecture between the central processing unit (CPU) and the memory is becoming ever more exacerbated, and the limitations of the computers compared to the brains are increasingly evident.[7,8] Unfortunately, this performance gap between the computer based on the conventional design paradigm and the brain based on naturally evolved mechanism cannot be bridged by simply sticking to the Moore's law that has dominated computing for more than half a century.[9–12] A new computing paradigm is on the horizon.

The concept of "neuromorphic electronics" was proposed by Carver Mead in 1990, aiming to reinvent computing by emulating the form of computation in the brain, such as the use of the elementary physical phenomena of semiconductor devices (i.e., transistors and floating-gate transistors) that bear analogy to the neural behaviors but have been underused in conventional digital computers as the computational primitives, as well as the use of algorithms that are more local to eliminate the "memory wall" problem, just like the brain.[13,14]

Neuromorphic electronic systems are complex and their creation requires the integration of sciences and technologies from different disciplines. To analyze such complex systems, it is legitimate and useful to reduce their rather high-level (coarse-grained) aspects into their lower levels (finer-grained), known as reductionism. The levels at which the complex systems are analyzed and understood are defined on a case-by-case basis. The multilevel analytical framework serves interdisciplinary cooperations by bridging different scientific disciplines and various theories together. Of course, there are logical and causal relationships among different levels. However, if the defined levels are only loosely related or epistemologically discontinuous, a straightforward explanation of the higher levels of the system in terms of the lower levels may not be allowed. In addition, it is a common feature of complex systems to give rise to novel emergent properties that are not predictable from the examination of individual components. Therefore, reduction is not omnipotent and must be supplemented with the synthesis of different parts.

To integrate parallel efforts that address the multiple aspects of the neuromorphic electronic systems efficiently, it is important to resort to an analytical framework consisting of several different levels, then clarify the position of each discipline, and develop a profitable integration strategy by using all or only a few selected levels, interactively or noninteractively.

Dating back to 1982, David Marr, a pioneer in computational neuroscience, put forth the three levels of analysis of the cognitive information processing systems: the computational, algorithmic, and implementation levels.[15,16] Marr's three-level framework has been reformulated several times in the subsequent decades[17–19] but still remains most familiar among cognitive scientists. One of the lasting influences brought about by Marr is laying out a framework for cognitive research and a method of analysis that enable the scopes of the problems to be defined in a tractable way, and enable the findings at one level to stimulate the progress at another. Separating explanations into different levels guarantees the most conservative estimates of to which level the computational machine is guaranteed to function correctly.[15]

Marr's three levels at which any machine carrying out an information-processing task can be understood are (**Figure 1**) as follows: 1) Computational level: at the computational level, the task to be performed is specified. At the checkout, for example, the task of the cashier is to calculate the total price of the items. 2) Algorithmic level: at the algorithmic level, the procedure of performing the task is stipulated. For example, the cashier can either randomly pick an item and add its price to the total or first group identical items together and then add up the subtotal price of each group which is the multiplication of the corresponding unit price by the quantity of items in the group. 3) Implementation level: the implementation level deals with the physical substrate embodying the algorithm. For example, underlying mental calculation is the biological neural network with its bio–physical–chemical mechanisms, whereas inside an

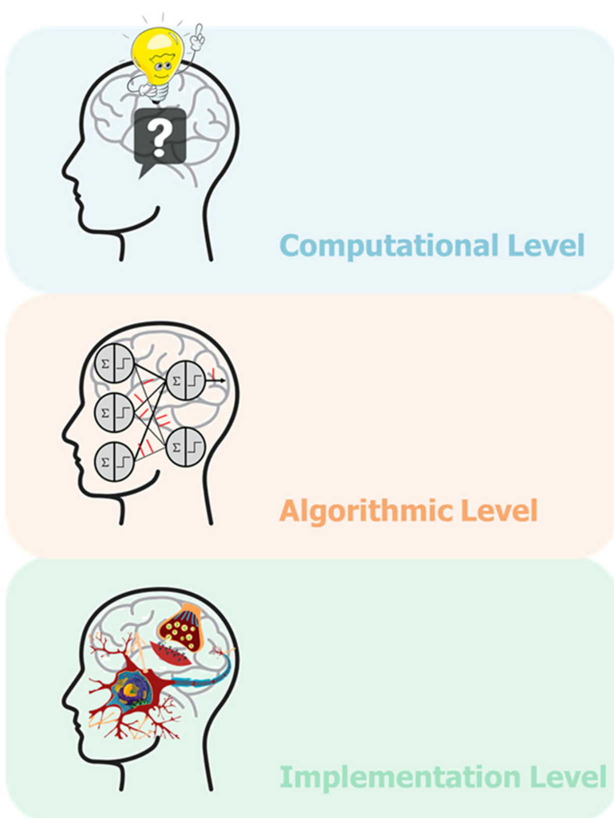

Figure 1. Schematic of Marr's three levels.

electronic calculator is the integrated circuit based on the semiconductor device principles.

Marr's framework has been very influential that a key methodology in cognitive science is proposed as follows: proceed by forming the levels of analysis that can be studied independently. These three levels of analysis are still the canonical scheme for organizing formal analyses of information processing systems over decades after they were first introduced.[20] A typical example of the benefits of the application of this framework to facilitate understanding, analyzing, and discussing research comes from the study of the cerebellar motor learning.[21] Motor control in animals requires constant calibration as the body changes continually. Cerebellum learns by evaluating the system's response to a given input against a desired outcome, and the deviation (error) is used to adjust the adaptive elements in the system.[22] Under Marr's framework, this is an example of supervised learning, computationally. To the top computational level down, knowing the structure of the environment and the information it makes available to the organism limits the types of information-processing algorithms that can utilize that information.[23] At the algorithm level, a well-known adaptive filter model[24] and the least mean square (LMS) supervised learning rule to adjust the weights have been proposed for the cerebellum. From the bottom implementation level up, however, knowing features of the implementation can help rule out some algorithms that might not be implementable and narrow down the search of algorithms given the components available.[23] In this specific case, the algorithms must be recast in forms that connect with the relevant neuronal implementation-level evidences for more detailed predictions about synaptic plasticity. For example, because the signs of the actual synaptic weights cannot be adjusted (positive for excitatory synapses and negative for inhibitory synapses), the model was updated to include additional inhibitory pathways with their synaptic weights corresponding to the negative weights in the original model. Experimentally, these synapses have indeed been found to be plastic in a way as required by the LMS rule.[21] Incorporating the spike-timing-dependent feature at the neuronal implementation level into the algorithm should permit more detailed comparison with experimental evidences.[21] This is one of the many examples of how research at each of Marr's three levels of analysis can constrain research at other levels.[23]

The usefulness of Marr's analytical framework has not only been demonstrated in the field of neuroscience but also been being appreciated by other developing fields of information processing technology. For example, Marr's levels of analysis have been suggested to be a powerful common frame-of-reference under which researchers can align perspectives and find common ground to drive forward progress in the field more effectively.[25]

Because of the clear organization of Marr's three levels of cognitive information processing and their demonstrated wide applicability to cognitive science, in this progress report we adopt Marr's three levels to analyze the neuromorphic electronic systems. The rest of the article is organized accordingly that the surveyed research endeavors are given significance from one or several of the three levels.

2. Computational Level

At the computational level, Marr advocated that "what" tasks the brain performs are to be specified. The function of the brain is not unaltered but evolves continuously through the interaction with the external environment. Equipped with a number of sensory organs and the capabilities of reflex/perception responses to the corresponding sensory stimuli, human neonates enter the world prepared to interact with it and survive it. As the newborn grows, it must learn new skills and remember useful life experiences to interact increasingly effectively with the world. As higher animals, humans have even more sophisticated computational tasks to perform, such as the use of language to communicate. Modern techniques have revealed the likelihood of these tasks being completed in specialized brain regions.[26] In contrast to the brain evolution that is driven by millions of years of genetic mutation and natural selection, building a neuromorphic electronic system can be an objective-oriented process with target tasks (brain tasks) specified in the first place, in light of the experiences of artificial intelligence (AI) practitioners who focus on building machines that solve AI tasks.[27,28] Even if the computation is (currently) not possible to be explained from the neural substrates, they provide constraints for the computation. Indeed, recent advances in neuroscience, such as neural intervention techniques, have presented the possibility of breaking the epistemological barriers between different levels.[29] In this section, we focus on three fundamental computational tasks performed by the biological brain, that is, sensory perception, learning, and memory. Their basic biological principles are introduced and the corresponding neuromorphic electronic implementations are surveyed. The computational perspective synthesizes these otherwise fragmented implementation-level research endeavors and provides them with a grander context.

2.1. Sensory Perception

Sensation is the process of detecting a stimulus, such as light and sound. Our senses begin with the conversion of the taken in real-world information from the receptors into electrical information that can be processed by the brain. The sensory information is then encoded by the activity of neurons, in the form of action potentials (also known as spikes), and travels to the central nervous system via structured pathways consisting of interconnected networks of neurons. There are various types of senses, each using different receptors that are sensitive to specific stimuli. Perception is different but closely related to sensation. It is the process by which the sensory information is interpreted and consciously experienced.[30] Although each type of sensation collects information corresponding to one attribute of the objective thing, perception is normally the reflection of various aspects of the object and their interrelationships. How the sensory information is interpreted is also subject to our available knowledge, experience, and thoughts. In a real biosystem, the boundary between sensation and perception is fluent that the end of sensation and the beginning of perception occur continuously. Due to the close link between sensation and perception, they are often referred to as sensory perception.

Different sensory perceptions are responsible for receiving, transmitting, processing, and eventually understanding different input stimuli, of which visual and auditory perceptions are the two main types of sensory perceptions. It has been estimated that more than 90% of the information is processed by these two sensory perceptions, and visual perception alone accounts for more than 80%.[31] In this subsection, only the biological principles of visual perception and its neuromorphic electronic implementations will be introduced and reviewed. However, other sensory perceptions and the multisensory perceptions are by no means suggested to be unimportant.

The visual pathway begins from the retina of the eyeball.[32] Photoreceptor cells convert light into electrical signals, which are then transmitted along the optic nerve fibers to the visual cortex, passing through a main relay point, the lateral geniculate nucleus (LGN). It is intriguing that, though the principal neurons in the LGN receive strong inputs from the retina, the strongest LGN inputs are from the cortex,[33] to which the LGN sends its output (**Figure 2**a).

The recurrence of the neural network supports two types of visual processes: the ascending (or feedforward, bottom-up) process directly carries out ever more complex analysis of the input with each successive stage in the visual pathway, whereas the descending (or feedback, top-down) process regulates the ascending process by means such as attention[34] and contextual guidance.[35]

Even in the absence of recurrent connections, the feedforward networks can perform substantial computations. The ascending pathway gives rise to receptive fields on the retina over which light can elicit LGN and cortical cell responses.[36] Over different receptive fields, which can be seen as well adapted to the structural features of the world, neurons perform weighted sum operations, with weights determined by the receptive fields, satisfying the requirement that the visual system should be invariant to the natural types of image transformations that occur in its environment.[37] In the visual cortex, it has been suggested that there are two processing streams,[38] the ventral stream from the striate cortex to the temporal lobe that is responsible for identifying what the object is and the dorsal stream from the striate cortex to the parietal lobe that is responsible for identifying where it is.[39,40]

As the level in the visual pathway becomes higher, the size and complexity of the receptive field structure also increase. The primary visual cortex (visual area 1, V1), which receives the visual inputs from the LGN, is responsible for low-level visual processing such as determining different types of contrast among visual scenes. The hierarchically organized higher-level visual cortexes are concerned with cognitive processes (interpretation and understanding) that associate information from a variety of sources with the visual information to form representation in one's consciousness.

Recurrence endows the network with richer functions. The descending pathway conveys higher-order information to

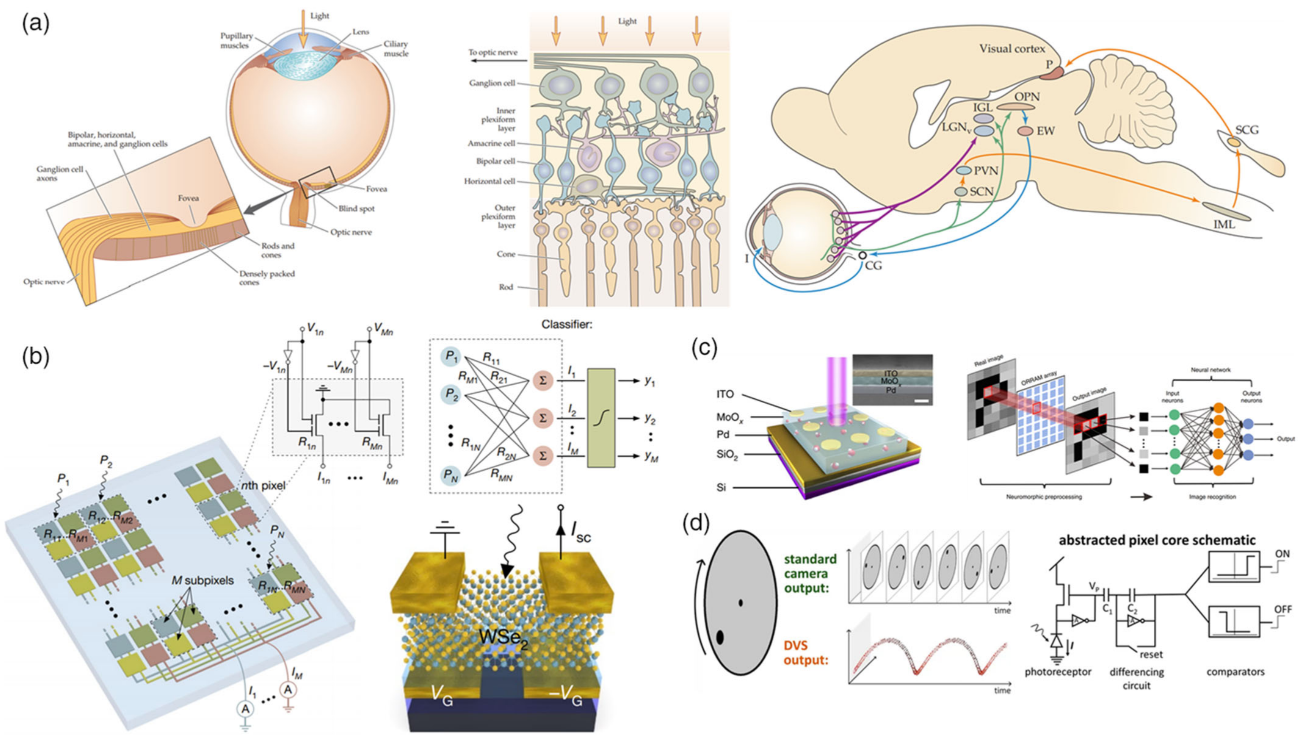

Figure 2. a) Close-up show of the neuronal organization of retina and schematic of the ascending and descending visual pathways. Reproduced with permission.[970] Copyright 2001, Sinauer Associates. b) Visual perception system based on 2D optoelectronic transistor array. Reproduced with permission.[246] Copyright 2020, Springer Nature. c) Visual perception system based on optoelectronic resistive random access memory (ORRAM). Reproduced with permission.[247] Copyright 2019, Springer Nature. d) Event-based image capture and dynamic visual sensor. Left and middle panels: Reproduced with permission.[972] Copyright 2018, Springer Nature. Right panel: redrawn from ref. [971].

antecedent cortical areas, influencing the earlier steps of ascending information processing. For example, by recalling the learnt information and encoding it in the descending signals, the resulting ascending signals can convey different meanings of the same visual scene according to the behavioral context.[35] Attention is another typical form of descending influence exerted on the ascending pathways, allowing neurons to carry information that is relevant to the current perceptual demands.[41] The receptive field properties are also subject to the descending influences. Over longer time periods, the receptive fields can change to accommodate alterations in visual experience.[35]

Early attempts at building neuromorphic electronic systems focused on the emulation of early visual processing in the retinas.[42–44] Photoreceptor cells in which the very beginning light–electricity conversion is accomplished are mimicked by optoelectronic sensors.[45–48] In series with standard silicon metal–oxide–semiconductor field-effect transistors (MOSFETs) operating in the subthreshold regions, logarithmic intensity to voltage conversion can be achieved, as in the photoreceptor cells. This realizes certain degree of independence of perception on the absolute illumination level and, instead, realizes the dependence of perception on the contrast ratio.[44,49] This is unlike the well-known charge-coupled devices (CCDs) and complementary metal–oxide–semiconductor (CMOS) sensors that report absolute brightness. Introducing adaptation mechanisms to further broaden the light intensity range (dynamic range) over which the artificial retinas can function has been a subject of great concern.[50–54] Due to technology advances,[46,55–103] sensory capabilities exceeding human limits in terms of sensitivity, speed, detectable spectrum, resolution, and so on may become possible. For digital neuromorphic processors, the electrical signals output from the optoelectronic sensors will be further digitalized via analog-to-digital converters (ADCs) for the next stage transmission and processing.

An artificial retina also mimics the fundamental plan of the human retina, that is, layers of neurons below the photoreceptors, including horizontal cells, bipolar cells, amacrine cells, and retina ganglion cells.[104] The lateral inhibition by horizontal and amacrine cells imposed on the direct ascending pathways mediated by bipolar cells, which gives rise to the unique concentric antagonistic retina receptive fields, is the most fundamental retina function to be emulated.[43,44] This has also inspired solutions to the dynamic range issue.[105]

A neuromorphic vision system can be the integration of either an artificial retina or any other kind of image acquisition device (e.g., camera), and a back-end higher-order visual processing hardware. According to the common wisdom in neuroscience, the output information from the front-end sensor array and the early visual processing circuit is transmitted to the back-end circuit where information is distributedly processed by neurons and synapses, and is stored where it is processed (synapses). So far, this is the fundamental motif adopted by any neuromorphic architectures, regardless of their different finer-grained implementations that are bio-plausible or not.[106] This distributed in-memory computing architecture is inspired by the highly intertwined biological neural network (Figure 2b).

Another typical topological characteristic of the artificial neural network (ANN) is the layered organization of neurons, which is used to extract a hierarchical set of increasingly complex features of the sensory information. The studies on the network map of human brain have also revealed many other network features, including high clustering and modularity with short path lengths which reflect a modular small-world architecture of the brain.[107] In fact, modularity assumption that anatomically and functionally distinct brain regions are responsible for the processing of different aspects of the sensory information is central to most theoretical and empirical approaches in cognitive science.[108] Modular neuromorphic electronic systems that divide the computations into several individual processing stages can be achieved by either monolithic integration[109] or chiplet assembly.[110–112] It has been believed that multichip systems (chiplet assembly) enable flexible implementation of more elaborate computational models without sacrificing the chip areas, and consequently, the processing abilities of certain stages, such as sensing, compared to single-chip systems (monolithic integration).[113] Monolithic 3D heterogeneous integration may realize high compactness and high functionality at the same time.

Neuromorphic vision systems are generally classified into two main categories: spatial vision systems and spatial–temporal vision systems.[49] The former kind of systems are designed for the spatial processing of static visual information, whereas the latter kind of systems are concerned with the time-dependent features of the changing visual information. In the past two decades, the processing functions of neuromorphic spatial visual systems have evolved from kernel-based linear filtering (e.g., convolution)[44] to highly nonlinear neural network computation.[114] Common computational tasks include edge detection, image compression, pattern classification, recognition, and so on (Figure 2c).[114]

For time-varying images (videos), vision systems can be further categorized into two types: frame-based and event-based ones.[115] The frame-based vision systems capture and process images frame-by-frame at fixed rates, whereas the event-based vision systems sense continuous flows of asynchronous spatial events, and respond as they occur or stay silent otherwise (Figure 2d). The event-based vision systems are more bio-realistic and feature lower latency, high dynamic range, and low power consumption.[116] At the level of sensation, an event-based vision system uses change detecting pixels to respond to brightness changes in the scene. The detection at each pixel is independent and asynchronous. As a result, the visual events (i.e., brightness changes) are converted into a sequence of electrical spikes. To transmit asynchronous spike signals, an efficient communication protocol, called the address-event representation (AER), has been proposed.[117,118] In AER, the address of the spiking neuron is encoded in a packet which is delivered through a multiplexed channel to the target neurons in other cores or chips via a lookup table. Using appropriate coding schemes, even the frame-based data can be converted to spikes or spike trains,[119] and vice versa.[120,121] Despite the convertibility between the frame-based data and spikes (or spike trains), the ultimate competence of the event-based vision systems should arise from their capability to process and perceive continuous input streams from the ever-changing real world, just as human brains do.[122] Currently, however, low-level visual processing tasks, such as optical flow estimation, motion segmentation, and recognition, are still the main application domains for both frame-based and event-based spatial–temporal vision systems.[49,116]

2.2. Learning and Memory

To interact increasingly effectively with the world, the growing newborn must improve its perception skill through learning. The record left by the learning process is memory; in other words, learning is a process for acquiring memory. Both learning and memory are primarily based on the mechanism of changing neuronal connections known as the synaptic plasticity.[123] Despite their interdependence, learning and memory are different. It is common that someone good at learning also has good memory, but not vice versa. This is because it is almost impossible for someone to truly learn something without also having the memory to retain what has been learnt, but learning goes beyond storing information. A good learner has effective learning schema, which may also have been learnt, to organize information, and, as often as not, to detect and construct relationships to the memorized knowledge or skills, which facilitates the acquirement of the new ones. In this subsection, the biological learning and memory principles and their neuromorphic electronic implementations will be introduced and reviewed.

2.2.1. Learning

Learning can be defined as a relatively permanent change in behavior that results from experience.[124] It occurs in all functional parts of the brain, including sensory systems, and at all levels of circuit organization, from spinal cord and cerebellum to cerebral cortex. It is widely believed that the brain learns by modifying the synaptic connections between neurons.

Many contemporary studies of learning are conducted in the context of its two basic types: nonassociative learning that involves learning from a single-stimulus experience, and associative learning that results from procedures involving two events.[124] In nonassociative learning, one's response to the single stimulus, as the stimulus is repeated, decreases (habituation) or increases (sensitization). Habituation saves individuals from consuming time and energy on irrelevant things, whereas sensitization reflects the instinctive biological need for vigilance and danger alert. There are also two main types of associative learning procedures, classical conditioning and instrumental conditioning. In classical conditioning, also known as Pavlovian conditioning,[125] which is named after Ivan Pavlov who conducted a Nobel prize–winning experiment on his dogs, a relatively neutral stimulus (e.g., the sound of bell in Pavlov's experiment) and a potent stimulus (e.g., dog food in Pavlov's experiment) are paired together (associated). As a result, the neutral stimulus alone can elicit the same response (e.g., salvation) that can be elicited only by the potent stimulus previously. Individuals learn to recognize and therefore prepare for imminent and biological significant events via classical conditioning. In contrast, in instrumental conditioning, also known as operant conditioning or trial-and-error learning, the behavior (response to a certain stimulus) is modified because it brings or is associated with punishment or reward. In most cases, behavior will be more refined and proficient after repeated trial-and-error practice.

To perform habituation or sensitization, conventional CMOS neuromorphic electronic systems use complex circuits composed of multiple devices.[126,127] With the advent of new non-CMOS devices, such as the memristors (see Section 4), these nonassociative learning behaviors are much easier to be implemented because their physical phenomena are in close analogy to the biological ones.[128–143] In these new devices, the relationships between the device conductances and the intensities (e.g., number of stimuli, amplitude, and duration) of the electrical stimuli are inherently nonlinear, mimicking either the habituation or sensitization phenomenon (**Figure 3**a).

Associative learning is more computationally sophisticated because it pairs different stimuli or pairs stimuli with existing memory framework, giving rise to updated memory frameworks for associative retrieval.[144] It has been a key function to be realized since the early stage of neuromorphic research.[145–166] During learning, the pairing (association) is achieved by the modulation of the synaptic connections according to certain learning rules. This forms new memory framework that stores the association information. During retrieval (i.e., perception), the ensemble states of neurons that are interactive through synaptic connections evolve collectively in response to the stimuli to a decision by reaching a new equilibrium state subject to the learned association.[167] Association achieved in this way possesses the capability of retrieving from noisy stimuli. Local Hebbian learning rules[168,169] that consider both the pre and post-synaptic activities are generally believed to be sufficient and necessary to enable associative learning. Therefore, most, if not all, of the neuromorphic demonstrations of associative learning are based on the implementation of Hebbian rules. However, the necessity of synthesizing Hebbian rules with presynaptic-only non-Hebbian rules[170] or global neuromodulatory mechanisms[171–173] has also been discussed. In the past decade, the emerging circuits with memristive properties have been of substantial interest for association function implementation.[174–194] Compared with conventional CMOS circuits, memristive circuits are more compact and the power overhead can be significantly reduced (Figure 3b).

Neuromorphic associative learning links new data (or information) to the existing memory framework and updates the framework by mapping the data to the neural network in a distributed manner. The data are retrieved by associating only partial data or noisy data, or by associating spatiotemporally or semantically correlated data with the memory framework. This is in contrast to the primary way of data storage and access in modern computers where data are stored in a deterministic address and are accessed on basis of the given address. As a special type of computer memory, association-based content-addressable memory (CAM), also known as associative memory, is used in networking devices where it speeds up searching for routing table lookup.[195–197]

According to the data used for association and memory recall, association can be categorized into autoassociation and heteroassociation.[198] Autoassociation is capable of retrieving a piece of data upon representation of partial content of that piece of data. As a special (and popular) form of ANNs, Hopfield networks have been shown to be able to perform autoassociation.[148,199,200] Ensembles of neurons that are responsible for memorizing a certain piece of data have recurrent connections between them. Autoassociative networks are useful for the storage of complex episodic memories.[201] Biological neural networks, in contrast,

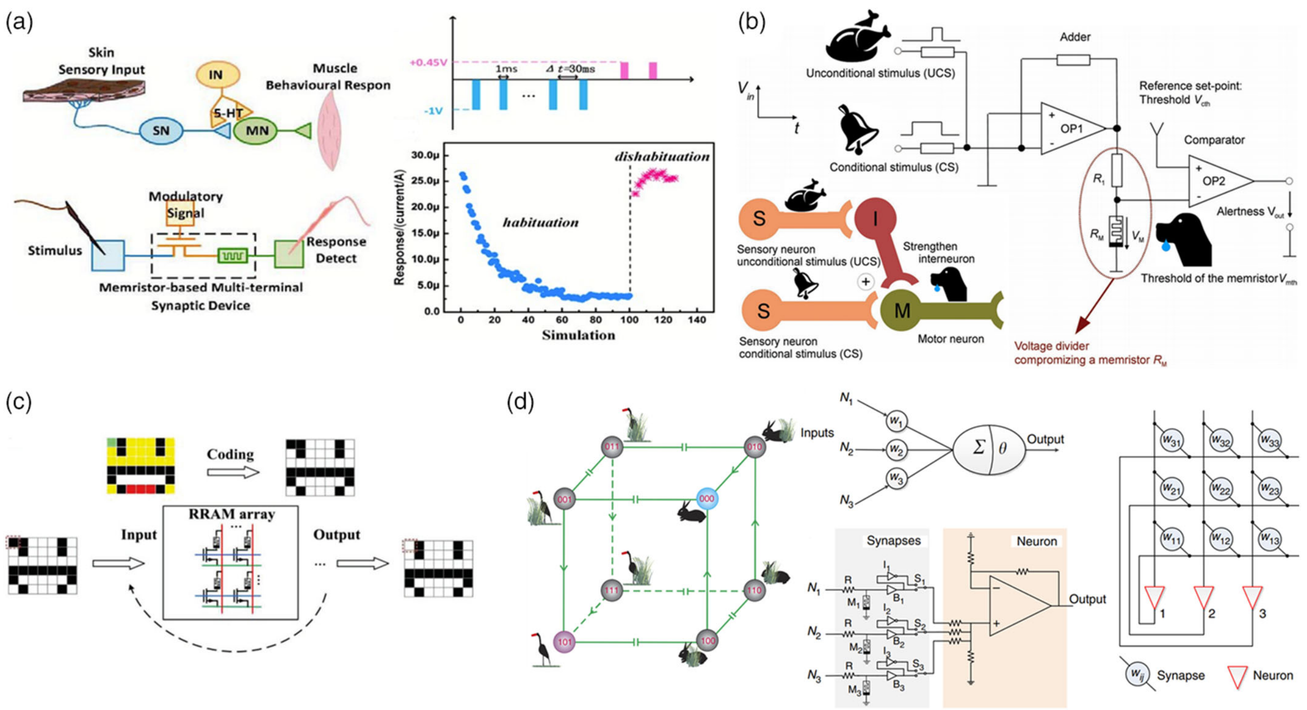

Figure 3. a) Nonassociative learning and its memristive device implementation. Reproduced with permission.[129] Copyright 2016, Royal Society of Chemistry. b) Associative learning (classical conditioning) and its memristive circuit implementation. Reproduced with permission.[176] Copyright 2012, Wiley-VCH. c) Autoassociation memory and its memristive Hopfield network implementation. Reproduced with permission.[211] Copyright 2019, Wiley-VCH. d) Heteroassociation memory and its memristive Hopfield network implementation. Reproduced with permission.[218] Copyright 2015, Springer Nature.

can also be heteroassociative because data can be retrieved upon representation of data from a different category. For example, when people see "banana," they may think of "monkey." The main difference to autoassociative networks is that recurrent connections are formed between two ensembles of neurons for the storage of different but correlated pieces of data.[202–204] Heteroassociation provides the advantage of retrieving sequences. In fact, episodic memory and sequence retrieving are related because the former is characterized by its compositional property and pattern sequences are equivalent to a single composition in a spatial–temporal context.[205,206] The relationships of theta sequences with episodic memories[207] and sequence retrieving[205] are important evidences for heteroassociative coding in the hippocampus.[173,206,208] Both CMOS and the emerging memristive implementations of autoassociation[209–211] and heteroassociation[212–218] have been demonstrated or proposed(Figure 3c,d).

2.2.2. Memory

Knowledge and skills are memorized for direct usage in the future or for easy linkage of new knowledge to the developing memory framework. Synaptic connections are the neuronal substrates for memory. All parts of the brain play a role in memory; among them, hippocampus and the surrounding structures embedded in the temporal lobe are found to be particularly important for the storage of new memories, and prefrontal brain regions are strongly associated with both the encoding of new memories and the retrieval of the old ones.[219,220] According to the content, memory can be classified as declarative (explicit) memory that concerns events and facts, or procedural (implicit) memory that concerns the use of skills,[123,221–224] reminiscent of the storage of the so-called data and program instructions in a von Neumann computer. Unlike the von Neumann computer where the same storage space is used for data and programs, it is believed that declarative memory (cerebrum and hippocampus) and procedural memory (cerebellum) require separate brain areas and use different mechanisms.[123,223,224]

Memories can also be classified according to their retention periods (**Figure** 4a).[225] Information can be temporarily hold in the sensory perception systems, which is known as sensory memory. This memory lasts a few seconds or less. The purpose of sensory memory is believed to briefly register information that is constantly taken in for it to be processed. Information stored in the sensory memory that is not further processed will be lost and can also be washed out by newly taken in information. The next stage of memory, short-term memory, receives information that is attended to from sensory memory. The retention period of short-term memory is from a few seconds to a few tens of seconds. Information stored in the short-term memory can be transferred to the long-term memory by rehearsal. As a specific type of memory that is intimately related to short-term memory, working memory is also extensively studied because it holds information needed to plan and carry out behaviors. As short-term

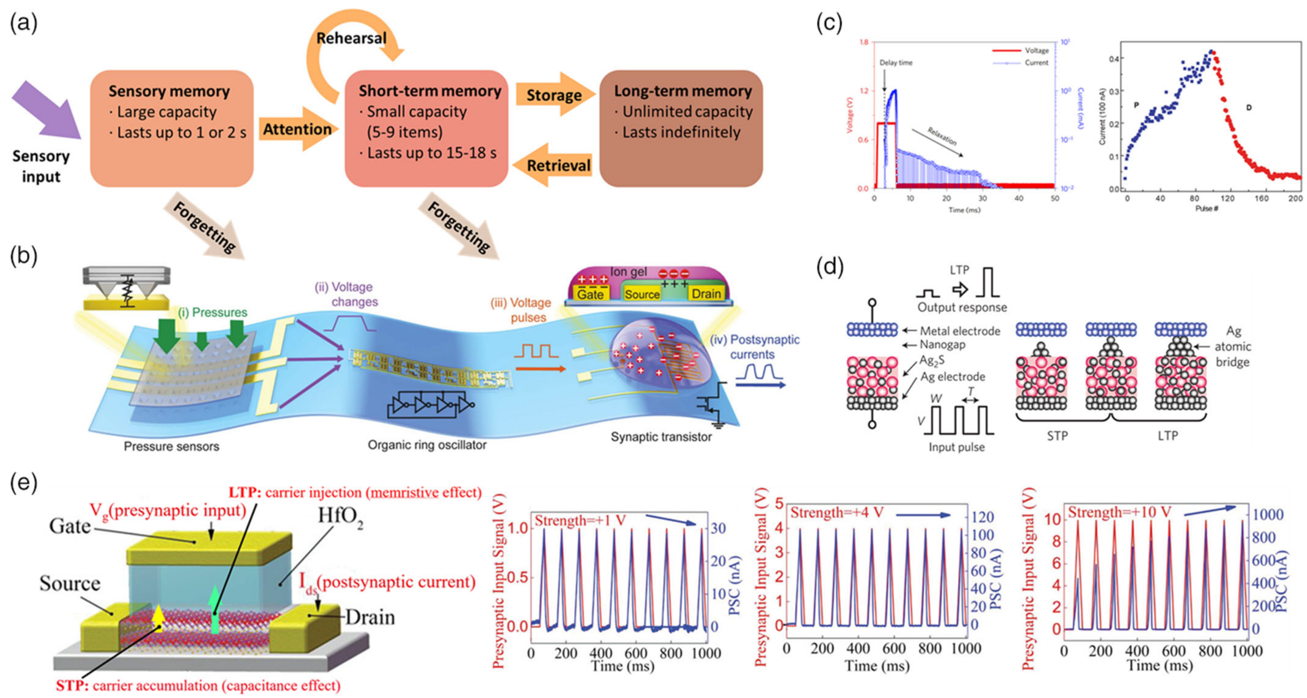

Figure 4. a) The transition process among memories over different timescales. b) Sensory memory based on organic neurons (oscillators) and synaptic transistors. Reproduced with permission.[252] Copyright 2018, American Association for the Advancement of Science. c) Short-term and long-term memory mimicked in diffusive and drift memristors, respectively. Left panel: Reproduced with permission.[273] Copyright 2017, Springer Nature, Right panel: Reproduced with permission.[382] Copyright 2010, American Chemical Society. d) Short-term to long-term memory transition in a two-terminal redox memristor. Reproduced with permission.[272] Copyright 2011, Springer Nature. e) Concomitant and independently expressed short-term and long-term memory in a three-terminal memristor (synaptic transistor). Reproduced with permission.[286] Copyright 2018, Wiley-VCH.

memory, working memory can only store information temporarily, but it is distinct from short-term memory that it concerns not only information storage but also the manipulation of the information selected into the focus of attention. A typical cognitive behavior reliant on working memory is dialing an unfamiliar phone number at the time of being told, the number is rehearsed over and over again to be sustained in the working memory until the last part of the number is retrieved and dialed. Long-term memory is a vast store of knowledge and a record of prior events. It differs from short-term memory by its long duration, often for days or even years. Not all long-term memories are equal, information with greater attached importance and being more frequently accessed can be recalled more easily.[222,226–228] In addition to the taken in sensory information, information in the long-term memory can be retrieved and held in working memory as well.[219]

Unlike a von Neumann computer that separates the memory unit from the processing unit, a neuromorphic electronic computer performs computation (perception) in memory. This is enabled by the neural network architecture. To be specific, computation is performed along the neural pathway on which each synapse is considered as an operator of weighted linear transformation and each neuron as an operator of nonlinear transformation of the spatial–temporal summation of all synaptic inputs. In the meantime, the computation parameters are stored right in these distributed computational units.

Another main difference between modern computers and neuromorphic electronic systems is that memories in modern computers are hierarchically organized according to their physical distances (near or far) from the CPU, or correspondingly, according to their operating speeds (high or low), or memory retentions (short/volatile or long/nonvolatile), or memory capacities (small or large), whereas in neuromorphic electronic systems memories are expected to be spatially separated on the basis of the stored contents, that is, declarative or procedural, not the physical properties of the memory substrates. This is understandable from the difference in the elementary memory components between the modern computer and the biological brain: the memory hierarchy of computer is essentially the result of the use of different semiconductor devices with fundamentally different physical mechanisms, whereas synapses as the cellular substrate of biological memory do not differ substantially from one another across the whole brain area in terms of the fundamental steps of memory formation, despite the difference in the detailed molecular mechanisms.[229,230] Instead of having memory components with either short or long data retention, neuromorphic electronic systems should have artificial synapses possessing data retention over multiple timescales concomitantly, mimicking the short-term and long-term plasticity of the biological synapses which is considered necessary for biological memory,[231] though not sufficient.[232–235]

Sensory memory is often thought of as the first stage of memory that binds intimately to the sensory organs. One of the most extensively studied types of sensory memory is the iconic memory (visual).[236] In addition to the differences in the information processing stage and the memory lifetime, sensory memory also differs from short-term memory in terms of memory capacity,[237–240] and maybe the subcellular mechanism.[241] Recent neuromorphic approaches to realize sensory memory are based on the short-term memristive phenomena in the emerging artificial synaptic devices. To distinguish between sensory memory and short-term memory, memristors possessing second-order or higher-order state variables are used so that the first-stage sensory memory is stored in the internal states of the devices, such as ion distribution, that the device resistances are unchanged, whereas the following stage of short-term memory is formed by the measurable resistance changes due to the accumulated changes of the internal states.[242,243] Recent reviews[244,245] have also surveyed the reports on the integration of sensors, artificial sensory neurons, and synapses[84,138,246–261] that suggest a trend of the integration of sensing, memory, and computing[262,263] (Figure 4b). Future neuromorphic electronic systems may also benefit from sensory memory in executing attentive novelty detection tasks and so on.[264]

Short-term memory has smaller capacity than does the sensory memory (virtually unlimited) that only the last few stored items in the sensory memory can be transferred to short-term memory. In addition to capacity, duration is also a limiting factor for short-term memory; otherwise, information smaller than the capacity limit could remain in short-term storage until they are replaced by other pieces of information, contradicting the short-term property.[237] In this sense, neuromorphic short-term memories should differ from the concept of volatile memory in modern computer whose only limiting factor is capacity. Spontaneous memory decay should be an important design consideration for neuromorphic short-term memory. Neuromorphic circuits based on CMOS devices have been used to implement the temporal decay effect of short-term memory.[265–271] With the advent of memristor devices, short-term memory can be implemented more compactly in single devices with intrinsic resistance decay properties (Figure 4c).[272–277] There are a wealth of spatiotemporal information processing functions enabled by the short-term effects.[278,279] Neuromorphic demonstrations of the functions of the short-term effects have mainly focused at the level of single artificial synaptic devices.[266,280–283] Neuromorphic systems are expected to benefit from the implementation of short-term effects at the circuit level and very large-scale integration (VLSI) level.[267,271,284–287]

Working memory is not completely distinct from short-term memory. Indeed, there are still confusing discrepancies in the usage of these two terms.[237] Here, to distinguish them, we refer to working memory as the attention-related aspects of short-term memory. Attention is required to prevent the system with limited information processing capability from fatigue or distraction. Attention can be either "top-down" controlled by current goals or automatically "bottom-up" attracted by the perceived properties of the stimuli (e.g., their salience).[34,288] The "top-down" attention is a limited resource, whereas automatic "bottom-up" attention is not thought to be resource demanding. The limited capacity of working memory has long been considered as a reflection of the limited resource.[289] Within working memory contents, a single item is often selected into the focus of attention for processing. It also contributes to controlling perceptual attention by holding templates for targets of perceptual selection, and contributes to controlling action by holding task sets to implement our current goals.[290] Interestingly, the unit of capacity of working memory is an integrated object rather than individual features comprising the object; in other words, the number of storable objects is, to some extent, independent of the number of features comprising the objects.[291] Neuromorphic electronic systems with "bottom-up" salience-based attentional mechanisms have been reported.[113,292–296] The selective attention was achieved by the global competition based on the winner-take-all (WTA, generally realized by inhibition) mechanism that automatically amplifies the strongest input signals and suppress the weaker ones, not requiring memory resource. Neuromorphic working memories have been achieved in the recurrently connected neural networks by the attractor dynamics that is self-sustaining even in the absence of external stimulation, thus preserving a "working memory" of past sensory events, until transitions between attractor states occur by stimuli.[269,297,298]

Long-term memory is probably the most familiar type of memory. According to the structural model of memory, that is, the multistore model,[225] long-term memory is the final stage that provides the lasting retention of information and skills. After rehearsal or repetition, information from the short-term memory can be transferred to the long-term memory. Although what the exact capacity of long-term memory is has not had a conclusive answer yet,[299–301] there is no doubt that the capacity is huge, if not unlimited. Long-term memory can be recalled into the working memory to be used when needed.[226,302] Memory recall is generally believed to be the reactivation of neuronal ensembles that constitute an engram.[303] Accordingly, major experimental evidences support the idea that the hippocampus acts as a temporary store for new information, but permanent storage depends on a broadly distributed cortical network.[304] Alternative views include the belief that although memories are encoded in hippocampal–cortical networks, hippocampus is always required in the retrieval of declarative memory,[305] as well as the belief that hippocampal-independent cortical engrams also exist.[306] Considering the huge memory capacity, the main constraint on recalling may be accessibility rather than availability. It is generally believed that memories that are frequently (less frequently) accessed become easier (harder) to recall.[227,228] It is also worth noting that the brain memory is also susceptible to errors at the system level.[307] The commonly alleged error tolerance of brain memory compared to computer memory (bit-level accuracy) is true at the synaptic level. Because it would be difficult to deny that each normal person has a rich set of long-term memories, the long-term memory is a natural part of a neuromorphic electronic system, generally stored distributedly in artificial synapses (Figure 4c–e).[13,308–316] There are also attempts to use separate long-term memory blocks to complement the distributed synaptic memory.[317,318]

3. Algorithmic Level

At the algorithmic level, the procedure of performing the task is stipulated. As the embodiment of the most abstract computational level, algorithm deals with the specific mechanism of computation, consisting of a set of actions to be executed to get the desired output. To decipher the neuronal algorithms, neuroscientists have conducted hypothesis testing experiments complemented by models and computer simulations to reveal what the interaction of the proposed component mechanisms actually entails and whether it can account for the cognitive function in question.[319] To date, algorithms can better capture either the aspects of the computational level or those of the implementation level, trading off cognitive fidelity against biological fidelity. From the computational level (cognitive science), algorithms are developed by decomposing cognitive processes into their computational components, giving rise to various important brain interpretations, such as the Bayesian brain; whereas from the implementation level (computational neuroscience), algorithms demonstrate how dynamic interactions between biological neurons can implement component computational functions, neural networks being the most well known. As the algorithmic embodiment of the computational function, the feedforward process or the inference process corresponds to the sensory perception function, whereas the error backpropagation (BP) process or the training process corresponds to the learning function.

The emergence and the substantial advances of machine learning have brought about an exciting opportunity for the design of algorithms. In machine learning, precisely designed codes are used for brute force optimization of the parameters of the ANNs toward minimized cost functions. Although neuroscience continues to play a role, many of the major developments in machine learning have been guided by insights into the mathematics of efficient optimization, rather than neuroscientific findings.[320] Although machine learning and neuroscience speak different language today, it has been believed that their integration will generate more rapid progresses in both fields.[27,321–325] In this section, we classify the neural network-based algorithms into two categories according to their design motivations, namely, the brain-like neural networks and the functional neural networks. Generally speaking, the former ones pursue biofidelity and attempt to justify the functional advantages, whereas the latter ones are function-oriented that the enabling working principles may or may not be bio-plausible. We introduce the basic neural foundations behind these network models as well as their basic working principles. Advances in these two fields are selectively surveyed.

3.1. Brain-Like Neural Networks

As introduced earlier, the vast synaptic connectivity is a hallmark of the biological neural network. This hardwired network supports neural algorithms that pay particular attention to the neuron activity-dependent information coding, node-to-node transmission, on-node processing of neuronal information, the adaption of synaptic connectivity, and so on (**Figure 5**a).

Different types of external stimuli are converted into electrical signals that can be processed by the neural system at the sensory receptors. Signals sent around the brain are carried by trains of action potentials (spikes) which are events of very brief rising and falling of the neuron membrane potentials caused by

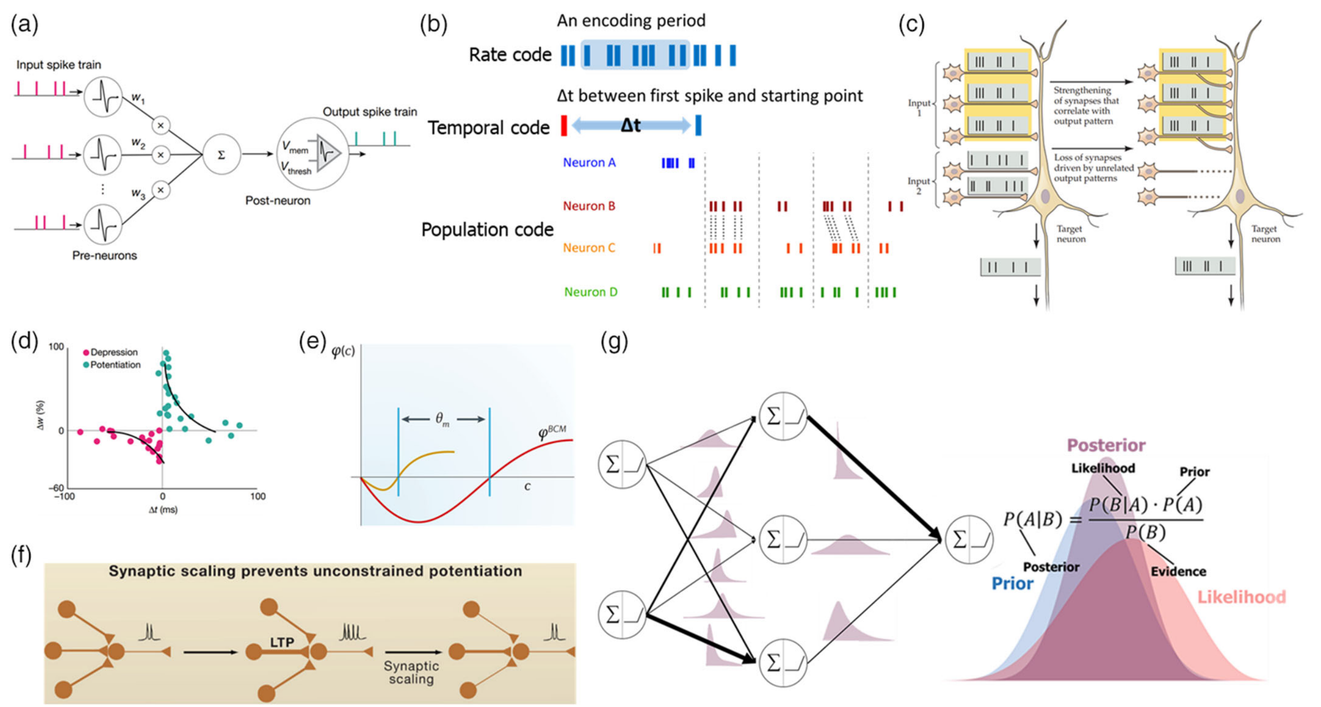

Figure 5. a) Schematic of a brain-like neural network composed of spiking neurons. Reproduced with permission.[122] Copyright 2019, Springer Nature. b) Schematics of rate code, temporal code, and population code. Reproduced with permission.[973] Copyright 2015, Elsevier B.V. c) Schematic of Hebbian learning rule (neurons that fire together wire together). Reproduced with permission.[974] Copyright 2017, Oxford University Press. d) STDP rule. Reproduced with permission.[122] Copyright 2019, Springer Nature. e) Sliding-threshold BCM rule. Reproduced with permission.[975] Copyright 2012, Springer Nature. f) Schematic of synaptic scaling. Reproduced with permission.[346] Copyright 2008, Elsevier B.V. g) Schematic of a Bayesian neural network with probabilistic uncertainty.

suprathreshold stimuli upon the neurons. There are many ways to quantify neural spike train data, including spike rate and spike timing. Neural coding concerns whether neural information is encoded in any of these quantities, with rate coding and temporal coding being the most extensively studied coding schemes. Information may not only be encoded in individual neural responses but also in ensemble responses, giving rise to the concept of population coding. There have been many evidences that the spike rate is physiologically relevant. For example, the strength of the flexion of an innervated muscle has been found to be dependent solely on the spike rate.[326] The receptive field of a neuron, as previously mentioned, is also determined mainly by observing the spike rate of that neuron in response to the stimulation of a specific sensory region.[327] There are many procedures of averaging to obtain the spike rate. Considering the relatively fast behavioral reactions, however, averaging over such short period of time does not guarantee the precision of the rate value. Instead of time averaging, averaging over a large population of neurons with identical properties may provide accurate rate value over such short-time interval because the population activity may vary rapidly and therefore reflect changes instantaneously.[328–330] In addition, the ability to encode probability distribution in the population codes gives rise to an important advantage of allowing the brain to perform Bayesian inference that accounts for uncertainty.[330,331] In contrast, candidate temporal coding strategies based on spike timing include those concerned with the latency between the stimulus and the first spike, the phase of the spike train with respect to the background neural oscillation, the synchrony of a pair or many neurons, and so on (Figure 5b).[328,332]

Neural information encoded in spikes is transmitted and processed along the neural pathways. As introduced in the last section, the processing of the sensory information is generally modeled as a hierarchy of increasingly sophisticated representations in function-specific brain regions or "modules." From an anatomical perspective, the hierarchy can be understood as the neuronal processing sequence. For example, the visual perception system consists of a sequential ordering of brain areas from retina to high-level cortical areas that are believed to be involved in the processing of the abstract aspects of the vision information.[333] Another interpretation of the hierarchy, from an information representation perspective, is the fine grain-to-coarse grain transition or generic-to-specific transition of information representation, say, from parts of the object to the full object as the information goes deeper in the network. In light of the latter interpretation of hierarchy, the two important characteristics of visual recognition, invariance and specificity, can also be modeled and understood.[334] Despite of the experimental advances of neuroscience in the past few decades, our understanding of the information processing principles at larger-scale neural circuits is still very limited.

Although feedforward network models can emulate a number of sensory perception phenomena, such as the emergence of cells that have simple and narrow receptive fields, as well as cells that have complex and broad receptive fields in the visual perception system (a natural result of the encapsulation of the fine-grained information in the coarse-grained ones along the network hierarchy), it is not sufficient to reconcile with the anatomy. As previously mentioned, in the visual perception system the dominant input to the LGN is not feedforward (bottom-up) from the retina but rather feedback (top-down) from the cortex. Therefore, feedback inputs are numerically prominent and cannot be ignored.[335] Recurrent neural network (RNN) has richer dynamics than feedforward neural network, and many cognitive functions are heavily reliant on this recurrence, such as the top–down attention, conscious sensations,[336] and decision making.[337]

Plasticity is another intrinsic property of the brain and it is the underlying mechanism for learning and memory.[338] Experiments have revealed a number of ways in which neuronal activities can affect the strengths of the synaptic connections, inspiring a variety of synaptic plasticity rules. More than 70 years ago, Donald Hebb[168] conjectured that if the spikes from one neuron always excite the spikes of the other, the synaptic connection from the former neuron to the latter should be strengthened. This theory is often summarized as "cells that fire together wire together" (Figure 5c). This original learning rule is, however, nonconvergent because it is only concerned with the increase in the synaptic strength. It has later been amended by pairing with the decrease in synaptic strength, such as the spike-timing-dependent plasticity (STDP) that correlates the relative timing of the pre- and post-synaptic spikes to the sign and amplitude of the synaptic change,[339–342] and by the compensation of homeostasis plasticity,[343–345] such as synaptic scaling,[231,346] as well as heterosynaptic plasticity.[347–349] Hebbian rule and many of its variants are local to the synapse being modified because they only care about the pre- and post-synaptic neuron activities. Although some local rules can account for homeostatic regulation, there is still debate on whether homeostatic regulation requires an explicit global renormalizing mechanism.[344,350] Moreover, a crucial question of how individual synaptic modifications according to these learning rules coordinate to achieve a network's goal remains to be solved if we are to truly understand learning in the brain.[351]

Because of the ability to encode temporal or rate information, spikes-based (spiking neural network, SNN) processing by physical pulse signals or by AER is generally believed to be a key signature of an electronic system that is neuromorphic, and at the same time, a main difference than real value-based machine-learning neural networks (commonly known as ANNs, and classified as functional neural networks in the next section).[122,352,353] Compared to ANN, SNN is generally believed to enjoy the low-power advantage partially due to the sparse interneuron information communication. However, spike itself can just be a superficial character of the neuromorphic electronic system because ANNs can readily be converted to their SNN analogues.[119,354–359] In general, the ANN-to-SNN conversion converts the real-valued data flows to the rate values of the spike trains.[360,361] The sparse interneuron information communication in the spike-based neuromorphic electronic systems is essentially related to the procedure of information processing in the spiking neurons, that is, firing an output spike only when the input spikes are integrated to a certain membrane threshold voltage, leaving all neurons not being active simultaneously. The stateful neuron with internal dynamics is also one of the key reasons of the aptitude of temporal processing in the brain.

By temporal or population averaging, rate coding losses rich information in the temporal dimension that is associated with the asynchronous nature of the interneuron communication.[362] In addition, because the spike times are continuous representations, the difficulty of differentiation in the scheme of discrete spike counts can be alleviated. Therefore, temporal-coding schemes and mixed rate-temporal-population-coding schemes have also been exploited.[356,363–373] Although rate and temporal codes can reflect the activities of individual neurons, population codes reflect their average (therefore fault tolerant) as well as their correlations.[329] The neuron couplings can also affect the timescale of information encoded in the population activities.[374] Population strategies have also been pursued by some developmental neuromorphic techniques.[375–378]

The temporal complexity of SNNs enables time-dependent learning rules, among which the STDP[339,341,379–381] is one of the most popular to the neuromorphic community (Figure 5d).[185,190,194,273,382–400] This learning rule is a specific type of Hebbian learning rule, which is local and unsupervised. However, directly training the neural networks by STDP is challenging because of the decreased spiking probabilities in deeper layers.[122] Hybrid local–global,[401,402] global,[368,403–411] and layer-wise[412,413]] learning approaches have been demonstrated. The global parts of the training procedures generally rely on the BP method.[414–416] Both the global and layer-wise trainings tend to use the rate values of the spike trains to approximate the real-valued neuron outputs, leading to mixed rate-temporal coding scheme when hybridized with the local STDP training.[362] Neuromorphic homeostasis strategies, including heterosynaptic plasticity, BCM (Bienenstock, Cooper, and Munro) rule (also known as the sliding threshold metaplasticity) (Figure 5e) and synaptic scaling(Figure 5f), have also been investigated to prevent the runaway of synaptic weights.[397,399,417–433]

The stateful neuron model with internal dynamics used in the SNN results in recurrent dependence of the network's state at a particular time step on its state in the previous time steps. This internal dynamics is intrinsically recurrent.[434] Dynamics can also be due to the explicit presence of recurrent synaptic connections between neurons in the network (i.e., RNN). RNN which captures more biological traits, that is, allowing neural activations to flow around in a loop over time.[435] The idea of RNNs was described shortly by Little in 1974[436] while its popularization has usually been accredited to Hopfield.[437] Because of the recurrent connections, the activities of the neurons in the Hopfield neural network keep changing over time till they have all settled down to some stable pattern that corresponds to a local minimum of the defined energy function behind the network dynamics. The number of patterns that can be activated manifests the storage capacity of the Hopfield network. These stored patterns also function as attractors toward which initial close-by patterns will dynamically evolve. The Hopfield neural network is useful for the implementation of the autoassociative memory function.[148,199,200,438–442] The idea behind is that when a memory clue (the initial pattern) is presented, the actual memory (the close-by attractor) that is most like the clue will be retrieved.[443] Hopfield networks have good noise and fault tolerance due to their dynamic nature.[444] Closely related to the Hopfield network, neural network named the bidirectional associative memories (BAMs) has been proposed to perform heteroassociation.[445–447] The BAM is the minimal two-layer RNN with intralayer connections only. Information passes forward from one neuron layer to the other with a potentially different size through the connection matrix M, then passes backward through the matrix transpose MT. In this sense, the Hopfield network can be viewed as an autoassociative BAM with two layers of neurons treated as a single layer. Over the past few decades, another type of RNN model known as the continuous attractor neural network (CANN), with some experimental evidences of its characteristics in the brain, has received broad attention from computational neuroscientists.[448] Its most prominent character is that it holds a continuous family of attractors rather than isolated ones as in the Hopfield neural network. Many computational advantages of CANNs have been revealed by theoretical studies, including anticipative tracking and multisensory information integration. Another fundamentally new paradigm of RNN modeling is the reservoir computing (RC). It has its predecessors in computational neuroscience[449] and has developed since 2001 from two independently proposed techniques, namely, liquid state machine[450] and echo state network.[451] The RC paradigm avoids the difficulties of gradient-descent RNN training by randomly creating an RNN (i.e., reservoir), which remains unchanged during training and whose activation state in response to the fed-in input corresponds to a nonlinear transformation of the input history, and training only the linear output layer. RC methods have become popular because of the improved accuracy, biological plausibility,[452] as well as the rich choice of physical implementation that any dynamical system has the potential to serve as a reservoir if it can exhibit dynamical responses to inputs.[284,285,453]

The coordinated synaptic weights across the network preserve neural coding scheme and the organization of excitatory and inhibitory inputs, that is, excitatory–inhibitory balance.[454,455] It has been believed that the inhibition of distracting information is closely related to attention control[456,457] and the dynamics in the network containing inhibitory neurons contributes to a wealth of information processing functions.[458–460] Inhibition as an efficient mean for computing has been widely used in neural network algorithms[461–465] or implemented in neuromorphic electronic hardware.[466–481]

Humans and other animals operate in a world of sensory uncertainty. Therefore, uncertainty or probability is another facet of our understanding of neural coding. There are rich evidences that human perceptual computations are "Bayes' optimal."[482] Frequentist inference and Bayesian inference are two general philosophies in inference statistics. Unlike the frequentist approaches that parameterize the inference models by maximizing the likelihood of the occurrence of the sample events (evidences), Bayesian approaches involve ones' prior beliefs (prior distributions) about the parameters before the evidences are considered, and maximize the posteriors as updated beliefs about the parameters after having seen the evidences. Spiking neuron models,[483,484] synaptic STDP models,[485] and population coding models[486] have been given Bayesian interpretations. Although many common machine-learning algorithms, such as logistic regression, use frequentist methods, a growing number of neural network algorithms have used Bayesian methods.[487–502] In general, Bayesian neural networks refer to probabilistic neural networks (by introducing probabilistic components into the networks, such as probabilistic neuron activations and synaptic weights) trained by Bayesian methods.[503]

There have been some hardware demonstrations or proposals of Bayesian neuromorphics.[489,504–509] Neuromorphic electronic systems are expected to benefit from Bayesian approaches in the integration of information over space and time, and the integration of information from different sensory cues and sensory modalities (Figure 5g).[482,510]

3.2. Functional Neural Networks

Although brain-like neural networks are constructed by piecing together bio-plausible (or as bio-plausible as possible) elementary computations and then functional developed, functional neural networks are designed to perform specific tasks and the network working (perception/inference and learning/training) principles and the computational elements may or may not be engineered in a bio-plausible way. The predecessor of neural network models is the McCulloch and Pitts's neuron model as a simple processor.[511] Single-layer perceptron (hardware) appearing in 1958[512,513] and adaptive linear neuron (ADALINE) in 1959[514] are the earliest forms of functional (pattern classification) neural networks that were designed along with objective functions to be mathematically optimized. Functional neural networks with a few layers of neurons appeared since then, commonly known as the ANNs (**Figure 6**a). With the depth of the network increased, the computing capability is also enhanced but at the expense of the increased difficulty of training/learning.

Modern learning algorithms can generally be classified into three categories based on whether the training data are labeled or not, namely, supervised learning (Figure 6b), unsupervised learning(Figure 6c), and reinforcement learning(Figure 6d) that is somewhat intermediate between the former two forms of learning.

During supervised learning, the error function that measures the error of the network output (trainee's answer) from the label (supervisor's answer) of the corresponding input is to be minimized. An influential method, BP, was described by Bryson and Ho in 1969,[515] Werbos in 1974,[516] and Rumelhart et al. in 1986.[517] This method enables the training of multilayer neural networks. However, historically it has been viewed as biological problematic. As another important step, neocognitron was introduced in 1988,[518] known as the first convolutional neural network (CNN), which was inspired by the experimental findings of visual receptive fields. It is a hierarchical neural network consisting of convolutional layers and downsampling layers whose units have increasingly larger receptive fields to encapsulate those of the previous layers. The approach of training CNNs by BP has become a foundation of modern computer vision and hearing system (Figure 6e).

Layer-wise pretraining, with each layer treated as an unsupervised restricted Boltzmann machine,[519] has been shown to be an effective way to overcome the well-known vanishing gradient problem[520,521] of BP training of the deep neural networks. During unsupervised learning, the network self-organizes in a manner that depends on the intrinsic nature of the training data set without the need of knowing the extrinsic labels. This technique spearheaded the field of deep learning. Similar unsupervised pretraining concept occurred earlier,[522–524] but for RNNs. Unsupervised pretraining has gradually been replaced by

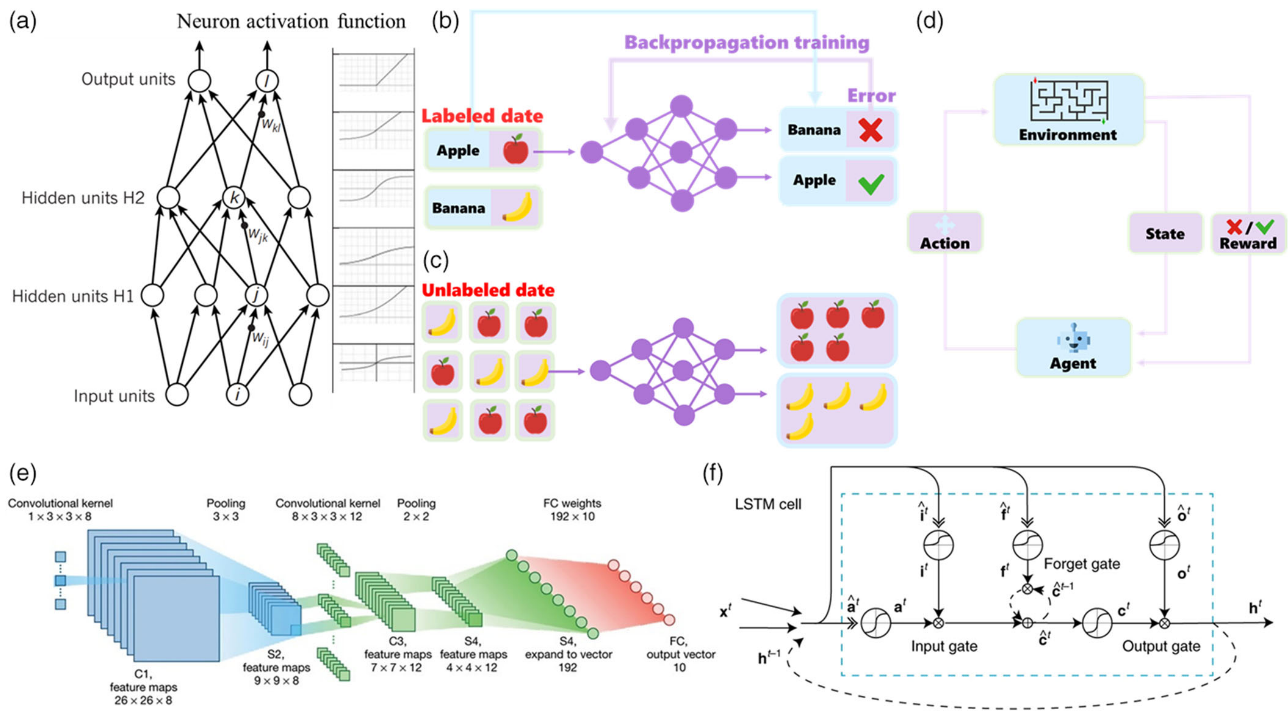

Figure 6. a) Schematic of a functional neural network and various neuron activation functions. Reproduced with permission.[593] Copyright 2015, Springer Nature. b–d) Schematic of supervised learning, unsupervised learning, and reinforcement learning. e) CNN for image processing. Reproduced with permission.[312] Copyright 2020, Springer Nature. f) LSTM network for time series information processing. Reproduced with permission.[903] Copyright 2019, Springer Nature.

simpler and effective methods of parameter initialization, such as batch normalization[525] and layer normalization.[526]

Unsupervised learning is expected to play key role in approaching human-level intelligence in view of humans' adeptness to accomplish tasks in an unsupervised fashion without having labels of the fed-in information.[527] Classical unsupervised learning methods for dimensionality reduction or clustering, such as principal component analysis, K-means, and so on,[528] are routines for computer vision. One of the most important outcomes of the application of unsupervised learning to neural networks is the autoencoder which aims to reduce the dimensionality of the input and reconstruct it with the least possible amount of distortion.[529–531]

Reinforcement learning is considered to be a more general form of learning, by trial and error, to act in unknown environments.[532–534] During reinforcement learning, the network output is not constraint by the standard answer (label) provided by the "supervisor"; instead, a feedback is provided in the form of reward or punishment to evaluate the appropriateness of the output. Accordingly, the value function that estimates the expected return is maximized over the action space.[535–537] The marriage of reinforcement learning and neural networks has given rise to many recent breakthroughs,[538,539] such as deep Q-network[540,541] and AlphaGo.[542–544]

Alternatives to the aforementioned learning algorithms are the evolutionary algorithms. Evolutionary algorithms evolve a population of parent models through mutation and crossover to gradually increase the fitness of the offspring models. More recent neuro-evolutionary approaches use evolutionary algorithms solely for optimizing the neural network architecture and use gradient-based methods for optimizing weights.[545–550]

In addition to feedforward neural networks, RNNs are also powerful models. Even the most classical Hopfield neural network model is applicable to solving many optimization problems, by transforming the problem into variables such that the desired optimization corresponds to the minimization of the respective energy function of the network.[443,551] The many variants of the Hopfield neural network, such as the Boltzmann machine,[552] have also been influential models in the development of deep learning techniques.

Due to the flow of neuron activations round over time via recurrent synaptic connections, RNNs are especially suitable for sequential data analysis. However, training an RNN is no easy task. Although BP also applies to an RNN that computing the gradient involves propagating information backward in time (i.e., backpropagation-through-time, or BPTT),[416] the learning problems with long-term dependencies have been shown to be difficult.[553,554] Long short-term memory (LSTM) RNNs are special RNNs that were introduced in 1997,[555] capable of overcoming the vanishing gradient problem without unsupervised pretraining. The unit of a LSTM RNN consists of a cell for memory and three gates, which is much more complex compared to the simple unit structure in the standard RNN. LSTM RNNs are now widely used for speech recognition, machine translation, and so on (Figure 6f). Its closely related variant, gated recurrent unit (GRU) networks, appeared later in 2014.[556] With increasing length of the sentence, the computational cost of the recurrent and CNNs to capture relationships between words grows significantly. To address this challenge, transformer networks[557–561] with simpler network architectures were proposed in 2017, based solely on attention mechanisms and dispensing with recurrence and convolutions entirely. It has now been widely used for text generation tasks with the trend of using larger models and more training data. Recently, spike-based RNNs have also gained increasing attention.[355,562–578]

Although the majority of the state-of-the-art neural network models are discriminative that simply discriminate between different types of data, their complements, the generative models, are useful when large labeled training data sets, which are the prerequisites for the discriminative approaches, are not easy to obtain. Generative models learn the data distributions of the training data sets so as to generate new data points. In contrast to the discriminative models that learn the conditional probability p(label | sample), the generative models learn the joint probability p(sample, label) (the conditional probability p(label | sample) is then obtained with the help of Bayesian theorem). One of the most topical generative models is the generative adversarial network (GAN)[579–581] in which a generative model and a discriminative model estimating the probability that a sample comes from the training data set rather than the generator are simultaneously trained in an adversarial fashion.

In addition to the aforementioned three classical forms of learning, other new forms of learning constantly join and supplement the library of learning algorithms for functional neural networks. These include the exciting concept of human-like transfer learning[582,583] that aims for generalization or knowledge transfer across related but different tasks, with the same network reused even when the training and test data sets have different distributions or features. This is also considered useful to deal with the problem of insufficient training data in some special task domains. In practice, given a target task, a source task from which the "knowledge" including the network structure and the connection parameters to be transferred is selected according to the information of the target task; the "knowledge" is transferred by directly duplicating part of the source-domain network or by learning how the source and target tasks are related (the transferable representations that are applicable to both the source domain and the target domain), using GAN-like strategy.[584,585] The idea of transfer learning has mainly been applied to supervised learning tasks and recently to reinforcement learning tasks.[586]

Closely related to transfer learning are multitask learning, lifelong continual learning, and metalearning. Multitask learning is different in that it treats all tasks equally and jointly optimizes these tasks,[587] and lifelong continual learning is different and can be more challenging in that it requires knowledge to be transferred across a sequence of changing tasks whose information is unforeseeable [lifelong machine learning]. Continual acquisition of incrementally available information from nonstationary data distributions generally leads to catastrophic forgetting[588] which can be mitigated by some solutions.[588,589] Metalearning, or learning to learn, is used to improve learning (including transfer learning) by dynamically searching for the best learning strategy as the number of tasks increases.[590,591] Metalearning is widely used for few-shot learning.[592]

Despite the tremendous success of machine learning in a variety of application domains,[522,593–595] many aspects of the algorithms have historically been viewed as not brain-like,[596] such as

BP. The past few years have witnessed growing research interest in integrating SNN and ANN,[315,322] enhancing the biofidelity of ANN[597–602] and exploring the biological significance of ANN.[27,320,325,603–611] Particularly, a hybrid of machine learning methods and neuroscience-oriented models also brings about fruits in various applications, including few-shot learning, multitask learning,[402] high-speed object tracking,[612] and even new AI chip architecture[315] with a combination of the effectiveness of the learning algorithms and the power efficiency of the neuromorphic devices. Looking ahead, the communication between neuroscience and engineering will mutually benefit each other.

For the moment, another major concern about the neural network models is their black box nature or unexplainability. In the light of this issue, explainable AI (XAI) by creating a second (post hoc) model to explain the first black box model has become a research area of interest in recent years.[613–619] As a further step, the necessity of developing algorithms that are inherently interpretable in the first place has been underlined.[581] Various approaches toward more transparent and explainable neural network computation have recently been proposed.[323,620–624]

To make the algorithms more hardware-friendly, several lightweight neural network models have been proposed, including quantized networks,[625–631] sparse networks,[632–636] tensor decomposition,[637–639] and hardware-aware neural architecture search.[640–642] A growing number of researches put emphasis on cross-layer optimization which enables algorithm–hardware codesign,[317,643–647] aiming at the optimal trade-off between energy efficiency and accuracy. It is expected that neuromorphic electronic systems will keep benefiting from advances in algorithms and the development of their supporting hardware platforms.

4. Implementation Level

The implementation level deals with the physical substrate embodying the algorithm. Richard Feynman famously wrote the following: "What I cannot create, I do not understand." So, do we now understand where the brain function comes from? This high-level question is frequently answered with how tremendous the number of neurons and synapses is in the brain, how neurons fire spikes, and what synaptic plasticity is.[648] These kinds of answers at the lower levels (finer grains) reflect a kind philosophy that (all of) the psychology can be reduced to its cellular and molecular causal mechanisms. In this philosophy, these elementary neural processes (physical implementations) are sufficient, though not definitely necessary, to ultimately produce high-level brain function. However, this philosophy is not undisputed. In fact, the debate between reductionism and other more holistic or more integrative approaches has been a long-standing issue in biological science.[649–651] It has often been argued that trying to understand brain function by understanding neurons is like trying to understand a bird's flight by studying only feathers. So, do details of the "feathers" matter or not? Although many psychological phenomena remain unreduced, neuroscience is indeed succeeding to the extent that it discovers more such reductions. Some neuroscientists believe that those unreduced for the moment may not be counterexamples to reductionism, but right there indicate that those related subcellular processes are incompletely understood,[652] including the plasticity of neurons as well as synapses, the pervasive and nonsynaptic communication between neurons via multifarious messengers, and the glia cells.

One of the typical phenomena in complex systems is the emergent phenomena that their parts do not have on their own but occur when the parts interact in a wider whole. This makes emergence a contrast to reduction. In neuroscience, it has also been a belief that the macroscopic/high-level behavior (cognition) can be ultimately understood as the emergent phenomena of the underlying neural collective.[653] A variety of dynamic phenomena can emerge in a neural network composed of neuron and synapse models even in their simplest forms.[352] Network neuroscience tries to provide an intuitively appealing network models for studying relationships among interconnected brain mechanisms and their relevance to behavior. Models span from biophysical realism to functional phenomenology.[654] Bio-realistic models include physically concrete (according to up to date bio-theory or empirical experimental data) elements, including neurons as the nodes, axonal projection patterns as the edges, and their experience-dependent changes (plasticity) should network development and regeneration be considered. These models are very elemental and fine grained. An advantage of bio-realistic models is that they incorporate rich empirical observations regarding the physical nature of the brain, but a disadvantage is that they could be difficult to interpret because of the large number of descriptive parameters. In contrast, network models of functional phenomenology have nodes and edges that do not necessarily have physical counterparts, and their evolutions are governed by laws in a more abstract and conceptual sense. They are not physical concrete but simple and informative. To make models even coarser grained, the smallest units may not be single spiking neurons but their ensembles with collective dynamics. These function-emphasized and coarse-grained models have been used for large-scale brain simulations. Intermediated between cellular/molecular systems and cognitive behavior in the environment, brain networks have been believed to mediate the causal effect of cells/molecules on behavior and vice versa.[655,656]

However, it has also been doubted whether network-scale studies are able to lead to the understanding of brain function.[657,658] The core question raised here is whether we should examine the physical brain (implementation) itself in the first place to understand the processes governing cognition.[658,659] It has been argued[658] that question "where the brain function comes from" is better approached through a behavior-driven manner, starting from task analysis (computational level), aided by theory (algorithm level), that allows behavior to be decomposed into separable modules and processing operations, and finally identifying possible implementations of the procedure through algorithmically inspired experiment.

Because of the obvious incompleteness of our understanding of the brain, there is a common question raised if we can really create a neuromorphic electronic system that functions like the brain.[660] The answer of this question depends on what neuromorphic electronic system is in one's mind. There are several understandings. Based on the first understanding, a neuromorphic electronic system is an electronic mimic of the physical brain that neuroscience knowledge at the implementation level is duplicated electronically (brain-like). This is a common neuromorphic research practice. In the last two sections, we have already seen examples of how advanced technologies enable electronic mimics of individual parts of the neural system with demonstrated simple computational functionalities. We do not intend to survey the neuromorphic hardware implementation again as this has been done in numerous reviews, just to name a few, at materials level,[48,661–722] at device level,[10,244,263,723–790] at more circuit level, or above.[106,114,158,445,791–808] In this research practice, the development of neuromorphic electronic systems is largely guided by the existing neuroscience knowledge, and fueled by the progress in neuroscience. So far, impressive progresses have been achieved in mimicking different forms of neuron dynamics (**Figure** 7a),[284,285,316,354,375,378,397,749,809–839] synaptic plasticity (Figure 7b),[197,265–277,667,749,804,838,840–860] passive dendrite processing (Figure 7c),[861–874] and neural network circuitry (Figure 7d).

It is worth mentioning that much of the current interest in neuromorphic electronics has been fueled by the emergence the memristive nanotechnology that holds promise for emulating the functions of the neuronal computing elements (synapses, neurons, dendrites, and so on) in a more natural way because of the adaptive and dynamic nature of the memristive materials and devices. The memristive phenomenon was first theoretically predicted by Chua in 1979[875] and its existence in experiment was first noticed in 2008 by HP Lab.[876] Unlike conventional CMOS devices and other textbook circuit elements, memristive devices have operation history-dependent electrical characteristics, governing by internal state variables evolving over time. Many working principles of the memristive devices are bio-explainable.[787,877] At the circuit scale, however, a practical integration issue known as the "sneak path issue" emerges. This issue can now be addressed by several approaches, including the use of an additional access device in tandem and engineering self-rectifying property into the device.[878,879]

Although most of these mimics are cellular-level phenomenologically oriented, more bio-realistic subcellular mimics are appearing.[286,855,880–885] Despite these progresses, there are still uncertainties as follows: neuroscience does not guarantee a foreseeable period of time in which the main mechanisms of brain function will be deciphered, or even the next breakthrough will take place to propel the progress of neuromorphic electronics to the next stage. Optimistically, neuroscience will continue to unveil more brain mysteries at different levels that are proved high-level function-relevant for neuromorphic engineers to mimic, and hopefully, the necessity and sufficiency of the biological substrates, at the network level or cellular level or even down to the subcellular level, in supporting brain function are finally justified.

More loosely defined, neuromorph does not necessarily mean brain-like but brain-inspired instead. Researchers holding this view embrace models of biophysical realism as well as models of functional phenomenology that may not be bio-realistic, as long as they lead to the system-level computational goals.[315,644] Indeed, many neuromorphic electronic systems have been designed with this view more or less in mind such as SpiNNaker[310,886,887] that consists of an array of commercial ARM cores not custom for neural network architecture. The neural models and the network topology are programmed to the hardware. Similarly, there is a wide research community centering on hardware accelerators for functional neural network algorithms.[888–891] Various types of hardware including CPUs,[892] GPUs (**Figure** 8a,b),[893–895] field programmable gate arrays (FPGAs),[896–900] emerging device-based circuits/chips,[196,284,285,311,312,316,479,768,769,796,798,806,895,901–934] and other customized processing units have been used to accelerate the full or a segment of the neural network algorithms. **Table 1**[313,314,935–939] is a performance comparison among these types of hardware. Conventionally, however, whether the hardware is claimed to be a neuromorphic hardware[308–310,313,315,940] (Figure 8c,d) or a neural network accelerator[936,937,941] (Figure 8e,f) largely depends on which design inspiration

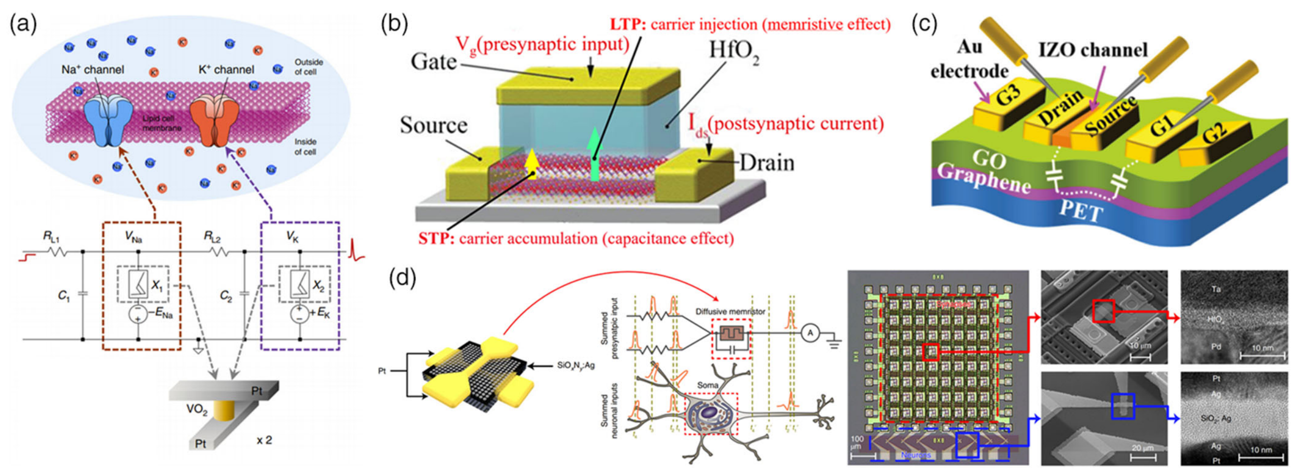

Figure 7. a) A neuron mimic based on memristive devices and other common electrical elements. Reproduced with permission.[836] Copyright 2018, Springer Nature. b) A synapse mimic based on three-terminal memristor (synaptic transistor). Reproduced with permission.[286] Copyright 2018, Wiley-VCH. c) A dendrite mimic based on multiterminal memristor. Reproduced with permission.[873] Copyright 2016, Wiley-VCH. d) An all memristive neural network mimic. Reproduced with permission.[829] Copyright 2018, Springer Nature.

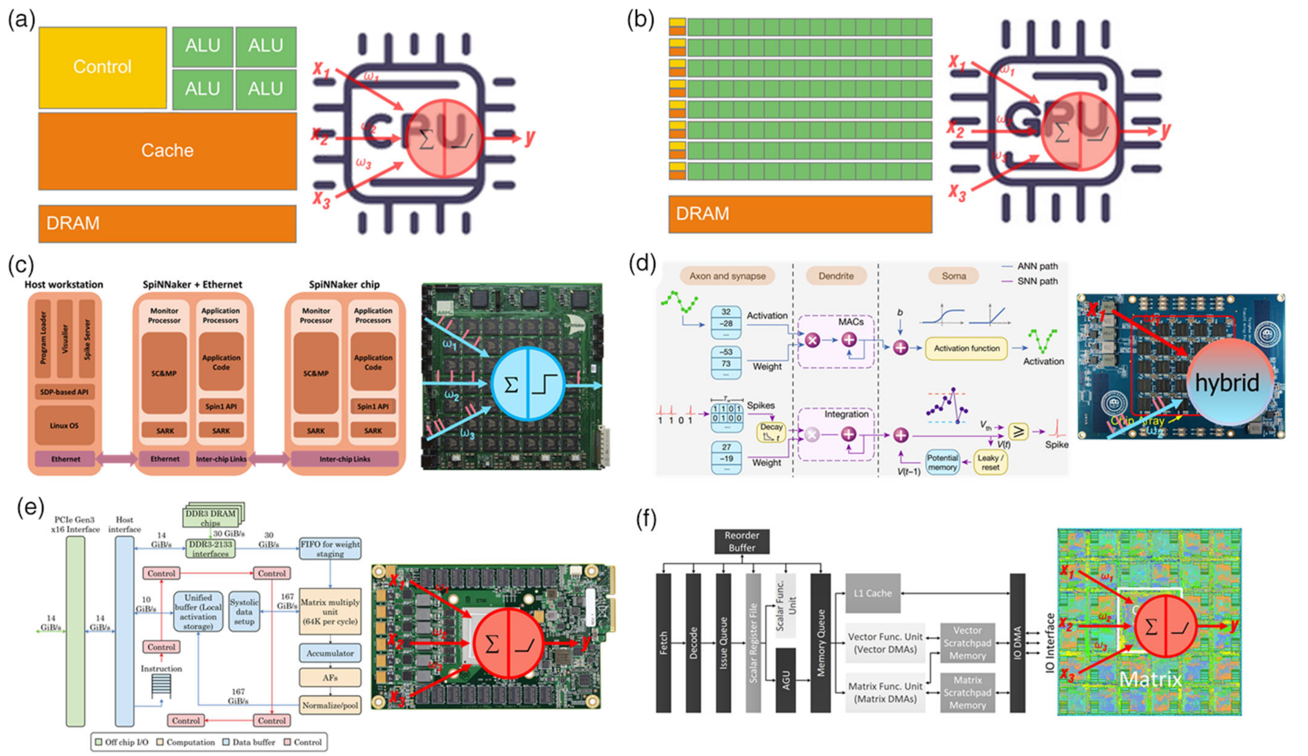

Figure 8. a,b) GPU and CPU accelerators for ANN. c) SpiNNaker neuromorphic chip array. Reproduced with permission.[310] Copyright 2014, IEEE. d) Tianjic neuromorphic chip array. Reproduced with permission.[315] Copyright 2019, Springer Nature. e) Tensor processing unit (TPU) accelerator for ANN. Reproduced with permission.[937] Copyright 2021, Elsevier B.V. f) Cambricon ASIC accelerator for ANN. Reproduced with permission.[941] Copyright 2016, IEEE.

dominates, the biological neural systems or the mathematics of the neural network algorithms.

Neuroscience has fueled the development of new electronic systems, vice versa? This is the motivation behind the third type of neuromorphic research, brain simulations.[942] The brain is a too complicated system to be fully understood solely by biological experiment without simulation. In the past century, massive neuroscience data have been accumulated. In contrast, the computation speed of the electronic computing systems has gone to the record 415.5 peta floating point operation per second (FLOPS).[943] Compared to the neural timescales, this is ultrafast and therefore it is feasible to consider the construction of biologically accurate models of the brain from first principles to aid our understanding of brain function. Important progresses toward this goal have actually been achieved through algorithmic approaches (**Figure** 9a,b).[944–948] In addition to algorithmic approaches, hardware implementations of the neural network architectures and their cellular components have the potential to make the simulations faster and more energy efficient.[949,950] With this consideration, many hardware platforms have served as not only information processing engines but also brain simulators (Figure 9c).[861,942,951–956] Compared to an actual brain, the neuromorphic system, either software or hardware based, also provides easy tractability of the real-time working status of its implementations at various scales using standardized means. In this sense, the neuromorphic electronic system may become a lab-on-chip platform for both experimental and computational neuroscientists.

5. Conclusion

The human brain is a complex system that has multiple levels of organization, so is a neuromorphic electronic system. In this progress report, we adopt David Marr's famous three-level analytical framework that was initially developed for studying the complex brain to analyze our selective surveyed research on neuromorphic electronic systems. By giving significance to these research endeavors from one or several of the three levels, the problem of how to build a neuromorphic electronic system is defined in a tractable way. Despite the rapid research progresses at the implementation and algorithmic levels, a major challenge is the inability to achieve brain-like (human-level) computational functions using current hardware implementations and algorithms. This is no surprise because neuroscience confronts similar challenge for long that extensive molecular/cellular-level investigations have not yet provided an answer to where the brain function comes from.

In fact, although Marr proposed the multilevel analytical framework, he in fact defended this hypothesis by expressing his reservations about the constructability of reductionism[16] and seemed to suggest that the implementation level is largely irrelevant. This is based on his viewpoint that these levels are

Table 1. Performance comparison among selected types of neuromorphic hardware or neural network accelerators.

Name	Number of synapses	Type of neuron	Number of neurons	Technology/material	Learning	Power consumption	Size/area
CPU (Intel Xeon W-1390 Processor)	–	Rectified linear unit (ReLU)/Sigmoid/tanh	–	14 nm CMOS	–	95 W (3.00 GHz)	1406 mm^2
GPU (GeForce RTX 3090)	–	ReLU/Sigmoid/tanh	–	8 nm CMOS	–	350 W (1.40 GHz)	628 mm^2
Cambricon[941]	–	ReLU/Sigmoid/tanh	–	65 nm CMOS	–	954 mW (544 GOP/s)	6.38 mm^2
TPU[937]	–	ReLU/Sigmoid/tanh	–	28 nm CMOS	Backpropagation	28 W (0.7 GHz)	<331 mm^2
Eyeriss[936]	–	ReLU/Sigmoid/tanh	–	65 nm CMOS	–	278 mW	16 mm^2
Neurogrid[308]	6×10^9	I&F	10^6	180 nm CMOS	STDP	941 pJ/synaptic operation	168 mm^2
SpiNNaker[310]	5×10^7	Leaky integrate-and-fire (LIF)	2×10^4	130 nm CMOS	Configurable spike-based plasticity	43 nJ/synaptic operation	101.64 mm^2
TrueNorth[940]	2.56×10^8	LIF	10^6	28 nm CMOS	Without on-chip learning	26 pJ/synaptic operation	4.3 cm^2
BrainScaleS[309]	10^9	AdEx	4×10^6	180 nm CMOS	STDP	–	50 mm^2
Loihi[313]	1.3×10^8	LIF	1.3×10^5	14 nm CMOS	Pairwise and triplet-STDP	23.6 pJ/synaptic operation	60 mm^2
Tianjic[315]	10^7	Hybrid	4×10^4	28 nm CMOS	STDP	ANN: 0.78 pJ/synaptic operation SNN: 1.54 pJ/synaptic operation	14.44 mm^2
Memristor[312, 920]	8192/16 384	ReLU	54/202	2 μm CMOS + nm memristor/130 nm CMOS+ nm memristor	In situ learning	15.6 pJ/synaptic operation/ 11 014 GOP s-1 W-1	–

only loosely related, and it is necessary and profitable to study the information processing of the brain at only a few selective levels but not all. In this sense, Marr's levels are less interactive, if not noninteractive.[957] Marr's levels were influenced by computer science. Most of the time, engineers can abstract from the circuits when designing the algorithms. However, even in computer science certain aspects of the algorithms depend on the hardware. It is believed that brains differ from computers in ways that exacerbate this dependence and it is not possible to understand cognition without considering its implementation.[319] Instead of being partial to one level over the others, more interactive approaches have also been suggested to strike a reasonable balance between the desire for a simplified model and the desire to incorporate as much of the known biological mechanisms as possible[958] and to productively constrain research at other levels.[23,957]

Marr's viewpoint is also a reflection of the status of neuroscience research in his times that no neurophysiological study (implementation-level study) had revealed new and clear correlation to high-level cognitive behaviors.[15,959] However, over the past few decades, neuroscience has been transformed.[960] With the development of many techniques, neuroscientists have begun to offer the causal-mechanistic explanations of the target phenomena as the outcomes of their component parts.[961] Two experimental tools are especially prominent in generating new data for the causal-mechanistic explanations in neuroscience: one is stimulating electrodes and [29,962] the other is optogenetics.[963] These new tools allow experimentalists to intervene into the workings of the components and to track the effects of these interventions on the target phenomena.[961] With these important additions to the reductionistic neuroscience of Marr's times, it is possible, although still arduous, to turn reductionism from merely descriptive to interpretive and therefore constructible.

In light of this, a Marr's three-level framework with more cross-level communications and interactions (**Figure 10**) is desired for understanding and driving forward the neuromorphic research (**Table 2**). In fact, growing importance has been placed on the codesign across multiple technological levels.[877,964–966] As an example, the different levels of research on memristive neuromorphic electronic systems have traditionally been less interactive that constrains at one level are put to the other unidirectionally from top down. Under the algorithm constraints (for a vast majority of the familiar algorithms), the "non-ideal" memristive properties, such as stochasticity and nonlinear weight-updating behavior, must be abandoned that required substantial efforts, although many of the discarded hardware properties can find their neuronal analogues. This previous less interactive approach to develop a neuromorphic electronic system may suffer from limitation at each level: at the implementation level, the biofidelity of the system unfortunately degrades; at the algorithm level, the model is far from simple as seen for instance by the fact that the modern functional neural networks are always heavily overparameterized and cumbersome peripheral circuits or external computing units are always needed to undertake the rest of the computing in addition to matrix

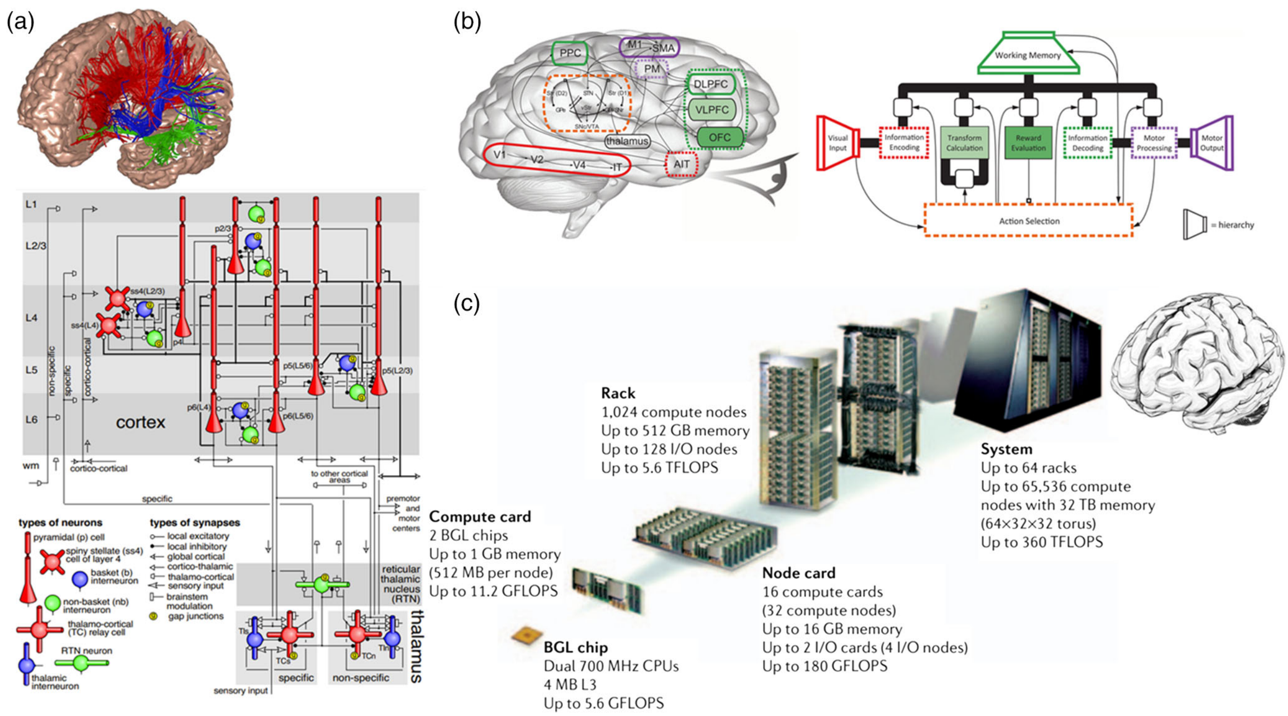

Figure 9. a) A large-scale neural circuitry model for mammalian thalamocortical system. Reproduced with permission.[947] Copyright 2008, National Academy of Sciences, U.S.A. b) The "Spaun" brain simulator. Reproduced with permission.[946] Copyright 2012, American Association for the Advancement of Science. c) The Blue Brain simulator. Reproduced with permission.[942] Copyright 2006, Springer Nature.

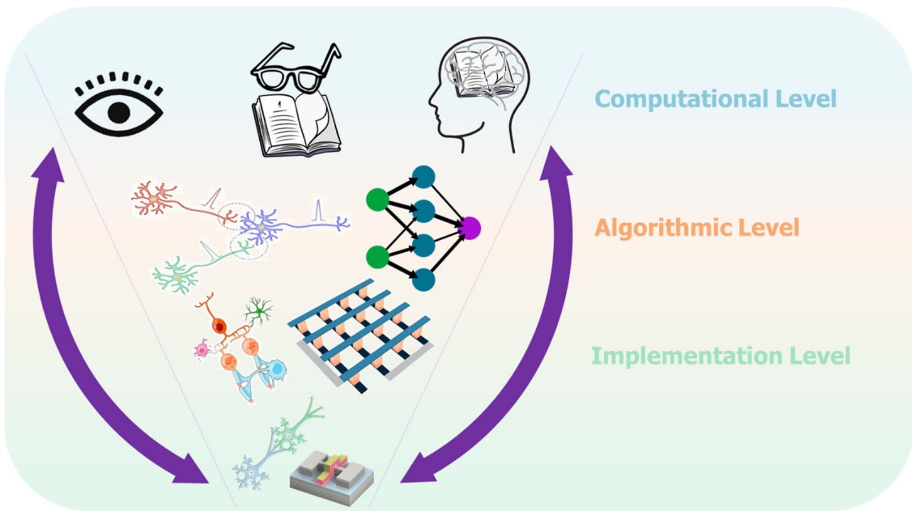

Figure 10. Schematic of Marr's three-level analytical framework for neuromorphic electronic systems.

Table 2. A category of references.

Level	References
Computational level	[26-318,382,970-972]
Algorithmic level	[27,119,122,148,168,185,190,194,199,200,231,273,284,285,312,315,317,319-647,903,973-975]
Implementation level	[10,48,106,114,158,196,197,244,263,265-277,284-286,308-316,318,352,354,375,378,397,445,479,648-900,901-956]

multiplication. In this context, the significance of adopting a more interactive approach has gradually been realized and a growing number of enticingly new neuromorphic functions have been being demonstrated by exploiting the intrinsic hardware nature for brain-like neural networks.[14,509,790,825,877,913,964–968] Communication and codesign across these different levels will fully unleash the potential of hardware implementations.

Under Marr's framework and adopting a codesign approach, the two seemingly different goals of mimicking the brain, that is, understanding the brain and conducting information processing, may become more aligned and be more likely to be integrated in a unified neuromorphic system[969]: at the bottom, it captures sufficient biological implementation details whose roles will be better understood in the context of the cognitive functions they support; at the top, it produces cognitive functions which are lower-level algorithms and hardware enabled. The potential neuroscience lab-on-neuromorphic chip platforms may accelerate neuroscience discoveries that in turn benefit the development of neuromorphic electronic systems.

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Conflict of Interest

The authors declare no conflict of interest.

Keywords

algorithm levels, codesigns, computational levels, David Marr, implementation levels, neuromorphics, three-level analytical frameworks

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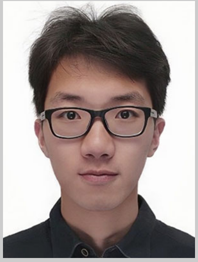

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