ARTIFICIAL INTELLIGENCE

Neuromorphic computing hardware and neural architectures for robotics

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Neuromorphic hardware enables fast and power-efficient neural network–based artificial intelligence that is well suited to solving robotic tasks. Neuromorphic algorithms can be further developed following neural computing principles and neural network architectures inspired by biological neural systems. In this Viewpoint, we provide an overview of recent insights from neuroscience that could enhance signal processing in artificial neural networks on chip and unlock innovative applications in robotics and autonomous intelligent systems. These insights uncover computing principles, primitives, and algorithms on different levels of abstraction and call for more research into the basis of neural computation and neuronally inspired computing hardware.

INTRODUCTION

Making robots and autonomous systems more intelligent in unstructured human-centered environments is one of the key goals in robotics, making it one of the most dynamic areas of technological development. The key ingredient of such intelligence is the ability to understand a complex and dynamic environment well and fast enough to reliably support other functions, such as motion planning and control; safe interaction with humans, objects, and other agents; and autonomous learning from experience.

Neuronal networks and data-driven training algorithms have opened two important windows into understanding the environment: image and sound processing (*1*). These algorithms achieve state-of-the-art performance on a large number of datasets, often even surpassing human performance, and are the primary candidates to enable intelligent perception and behavior in robotics (*2*). However, robotic use cases pose particularly strict demands on power consumption, latency, adaptivity, and data efficiency of artificial intelligence (AI) algorithms (*3*, *4*). Today, despite the advantages of neural network–based algorithms compared with the previous hand-crafted AI solutions (*5*, *6*), we are still lacking truly intelligent and agile robots capable of safely and smoothly interacting with objects, each other, and humans in our daily lives. This stands in stark contrast to even simple animals that can produce intelligent behavior and interact in complex real-world environments. Animals can quickly switch between tasks and adapt to a large variety of conditions, often relying on small and efficient neuronal networks (anecdotally, even the human brain consumes around 20 W of power with its 80 billion neurons). Can we achieve similar performance with neural network–based algorithms if we look closer at how biological nervous systems tackle the problems of perception, movement generation, and learning?

Artificial neural networks were originally inspired by biological neural systems. They compute by passing activation in a massively parallel network of simple units that sum incoming signals and compute a nonlinear, threshold-based function to produce an output. This computing model is very close to the early mathematical abstraction of biological neurons, e.g., the McCulloch-Pitts neurons from 1943 (*7*). Although this computing paradigm mimics computation in the brain on some abstract level and certainly comes closer to how biological neural systems function compared with conventional software and algorithms, modern computational, cognitive, and systems branches of neuroscience have delivered a plethora of new insights about biological brains over the past seven decades. Some of these biological computing principles, we argue, are crucial for making animal brains as power-efficient, adaptive, robust, and autonomous as they are. By uncovering some of the key computing principles and algorithms (neural network structures or architectures) of biological neural systems, we could further enhance performance of artificial neural networks in robotic tasks.

One particularly striking difference between biological neural systems and artificial neural networks dominating the AI space today is the way in which artificial and biological neural networks learn. Error backpropagation is a powerful and generic function approximation algorithm that led to impressive results in approximating complex functions in image or sound classification tasks. However, it does not reflect the learning dynamics and the development of biological neural systems, nor can it approach their flexibility, versatility, and ability to learn continually. Overcoming the limitations of the error backpropagation–based training—such as its offline character and rigid nature of the trained networks, catastrophic forgetting, data-hungry procedures, and limited generalization and abstraction capabilities—is one of the key tasks tackled by AI and machine learning today. Solving them is particularly important for robotic applications, for which learning from experience and observation as well as continual adaptation to changing conditions are more natural learning paradigms than offline training with labeled data. The biological mechanisms for adaptation and learning could bring new inspirations in this domain.

Another important insight about biological computing is that the computing hardware matters. Although today's computers are universal computing machines and can compute any algorithm, including artificial neural networks, the efficiency of the implementation suffers from a mismatch between the low-level structure of the computing hardware and the algorithm that it runs. This has been pointed out by researchers in the field of neuromorphic engineering for decades but could

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be safely dismissed as long as conventional computers were becoming faster and gaining more memory every year, following Moore's law. Today, as Moore's law reaches the physical limits of how small the transistors can get while still ensuring reliable computation, neuromorphic hardware offers one of the best matches to modern biologically inspired computing algorithms (*8*–*11*). It has been shown that these hardware systems allow us to gain orders of magnitude advantages in computing speed and power consumption for simulating brain-like spiking neural networks (*12*)—the two performance identifiers of particular relevance in robotics. These advancements rely on fine-grained parallelism of neuromorphic hardware; co-location of memory and computing; event-based asynchronous communication between computing elements; and the implementation of elemental temporal neuronal, synaptic, and learning dynamics (short-term and long-term plasticity) in an efficient way using modern digital or analog computing technology (*13*–*17*).

To use this unconventional computing hardware to solve real-world robotic tasks, we need to "program" neuromorphic devices, i.e., find network structures and learning rules that solve relevant tasks in the same reliable and adaptive way as animal brains and bodies solve them and that, at the same time, lead to algorithms that can be benchmarked and achieve state-of-the-art performance. To arrive at this vision, the three fields need to interact more closely: robotics providing the understanding of the use cases and their challenges, neuromorphic computing enabling the efficient implementation of the required computing elements, and computational neuro- and cognitive sciences providing computational insights into biological computing principles.

In this Viewpoint, we assess the state of the art in neuromorphic computing and engineering and provide an overview of bioinspired computing principles on different levels of computing hierarchy that can lead to a new generation of neuromorphic computing systems to enable smarter robots under strict power, latency, and form factor constraints. We then consider how neuromorphic computing technology has been used in robotics so far and provide a vision of how it could be deployed in this field in the future.

NEUROMORPHIC COMPUTING HARDWARE

Biological brains constitute a computing "hardware" that differs from today's predominant von Neumann computing architecture in a number of important ways. First, in the brain, there is no distinction between the processing unit and memory. In biological neural systems, variables (i.e., signals, measurements, or parameters) are stored as properties of neurons and (synaptic) connections between them, and the same neurons and synapses perform the computing operations. Thus, there is no "von Neumann memory bottleneck"—the separation of memory and central processing unit (CPU)—that drains energy in today's computers when running neural network–based algorithms (*18*).

Second, biological neural systems represent values of variables in a distributed manner in a network of computing elements, each of which can be an "unreliable" biological cell with stochastic internal dynamics. To the contrary, in today's computers, a lot of resources are spent on making individual elements reliable and computation exactly reproducible. The distributed representations enable a more flexible and adaptive allocation of resources to represent signals with different precision, or resolution, depending on the sensor modality and task.

Third, the internal dynamics of biological neurons and synapses unfold in time, making computation inherently temporal and stateful (*19*). Such neural dynamics are linked to real physical time and can be integrated easily in the sensorimotor control loops. Computation can unfold on different time scales in different parts of the architecture and does not require a global clock that commands when the next operation should be performed. Each unit integrates its input continuously in time and communicates relevant signals when those are detected using "spikes" (brief activity bursts) in an asynchronous manner. Because signal communication is an expensive operation, making such communication sparse and targeted, or event-driven, makes computation more energy-efficient.

Neuromorphic computing hardware implements such computation, grounded in the dynamics of spiking neurons and dynamic synapses, efficiently with analog or digital electronic circuits (*8*, *10*, *11*, *20*). Undoubtedly, the full complexity of signal processing in biological neural networks is beyond our current ability to instantiate it in hardware. However, the experimental neuromorphic hardware platforms available today can emulate some key structural components of biological neural networks, which are remarkably conserved across different animals from worms to humans (*21*–*24*).

Similar to biological neural networks, information processing and storage take place in neurons and synapses on a neuromorphic chip. Neurons integrate inputs in a continual manner, often with nonlinearities realized with dendritic "compartments." The analog-to-digital signal transformation happens when an integrated input reaches the activation threshold, which results in spike generation. Spike-based communication is more reliable than analog communication of signals. Most neuromorphic chips emulate the typical leaky integrate-and-fire dynamics of neurons (*8*, *25*). Mixed-signal neuromorphic devices use analog circuits to emulate the dynamics of neurons and synaptic connections (*26*, *27*). The binary spikes in these systems are communicated as digital signals using the address-event representation, i.e., a spike carries a digital package with the address of the emitting neuron. The address is used to deliver the spike to its destination in the digital routing circuitry (*28*). A system of routers or a network-on-chip brings spikes to their destination neurons. At the destination, the binary spike is "unpacked" by the synapse as an analog signal that is injected into the postsynaptic neuron over time with exponential decay. The resulting mixed-signal neuromorphic systems emulate the continuous temporal dynamics of biological neurons (*11*, *15*–*17*, *29*–*31*). Table 1 lists some of the neuromorphic computing platforms available today with their key characteristics.

Recently, alternative materials and electronic devices are being explored that have a memristive property: the ability to hold the state induced by a transient spike. These memristive devices could make analog neuromorphic circuits even more efficient and compact in the future, when technological challenges of variability and reliability of such devices are overcome (*32*). There are several laboratories and startups that develop mixed-signal neuromorphic computing hardware, harnessing its ultralow power, adaptivity, and continuous in-time computing (*17*, *29*, *33*).

Another approach to neuromorphic hardware, adopted by the semiconductor companies, is based on the conventional digital complementary metal-oxide semiconductor technology. Digital circuits can efficiently implement the key characteristics of neuronal computation—the event-based sampling of signals—and run the required neuronal dynamics in simple cores with local memory. Digital circuits have an advantage of time multiplexing, which allows the chip designers to integrate many more synapses and neurons

Table 1. Overview of some of the neuromorphic chips available today. 1 K = 1056; 1 M = 1 million; Y, yes; N, no; SNN, spiking neural network; HPC, high performance computing.

Company/Lab	Chip type	#Neurons/ synapses	On-chip learning	Power	Software	Applications
ROLLS (*16*)	Mixed-signal	256/64 K	Y	~5 mW	Custom python	Research
DYNAP-SE (*15*)	Mixed-signal	4 K/4 M	N	~5 mW	Custom python	Research
NeuroGrid (BrainDrop)/ Stanford (*29*)	Mixed-signal	1 M/billions	N	~3 W	NEF	Real-time SNN emulation
Innatera	Mixed-signal	256/64 K	N	~1 mW	PyTorch	Smart sensing
BrainScaleS 1/ Universität Heidelberg (*17*)	Mixed-signal	~180,000/40 M (in 352 chips)	N	~300 W	BrainScaleS OS	Accelerated SNN emulation; HPC
BrainScaleS 2/ Universität Heidelberg (*30*, *31*)	Mixed-signal	512/~130,000	Y	~1 W	BrainScaleS OS	Edge processing, robotics
TrueNorth/IBM (*9*)	Digital	1 M/256 M (in 4 K cores)	N	~0.3 W	Custom	DNN acceleration
SpiNNaker/University of Manchester (*13*)	Digital	1B/10 kilobytes (in 64 K x 18 ARM cores)	Y	~kW	PyNN, NEST	Real-time simulation of SNN; HPC
Loihi/Intel Labs (*12*)	Digital	~128,000/128 M per chip (scalable)	Y	~1 W	Lava	Research chip
Dynap-CNN/ SynSense	Digital	~327,000/278,000	N	~5 mW	Rockpool, PyTorch	Smart sensing
BrainChip/Akida	Digital	Configurable, 8-Mb SRAM	Y	~30 mW	TensorFlow, CNN → SNN	Smart sensing, one-shot learning
Tianjic/Tsinghua University (*34*)	Digital	40,000/10 M (on 156 cores)	N	~1 W	Custom	ANN/SNN acceleration

into the same amount of silicon area. Multiplexing the routing network allows a great range of network topologies. Examples of such platforms include SpiNNaker, developed in the neuromorphic computing pillar of the Human Brain Project (*13*, *14*); Loihi, a neuromorphic research chip from Intel (*10*, *12*); TrueNorth, the first widely distributed neuromorphic chip from IBM (*9*); the Tianjic chip (*34*); or the Dynap-CNN chip from the company SynSense (*35*). Table 1 lists some of these devices. A recent review has demonstrated that this type of hardware shows several orders of magnitude advantages in the energy-delay product on many workloads, in particular those relying on recurrent neural network architectures (*12*).

Figure 1 shows how both ultralow-power, small mixed-signal, and larger-scale digital devices can be used in different parts of the robotic signal processing and control pipelines. Thus, ultralow-power, mixed-signal, or analog devices, such as proposed by Innatera or the ROLLS/DYNAP-SE family from University of Zurich and SynSense company, or the HBP development BrainScaleS, to name just a few, are well suited for embedded signal processing in an always-on setting or for local processing on a particular sensor or motor unit. The larger-scale digital devices, such as SpiNNaker or Intel's Loihi, can take more elaborate workloads, integrating multiple sensory channels, processing high data rate visual information, or solving optimization tasks of motion planning and control.

To move the frontier of neuromorphic computing to the next level, several functionally important characteristics of biological neurons, synapses, and networks could be supported in hardware in the future. For instance, although spike-based communication is commonly used in neuromorphic computing (*10*, *13*, *36*) and modeled in computational neuroscience (*37*–*39*), it is not the only form of information propagation in biological networks. Electrical synapses (*40*), for example, enable the direct exchange of ions between neurons, allowing analog communication and network-wide propagation of signals, resulting in waves, oscillations, and other dynamical patterns. Neuromorphic implementation of electrical synapses could simplify the computing architecture, reduce energy expenditure, and help transfer information across large neural networks. Such implementation has been attempted recently in the NeuroGrid neuromorphic device (*29*).

In real biological networks, the short-term synaptic dynamics, with a slow decay time course in the range of 50 to 150 ms (*37*, *38*), limit the spiking rate in most neurons to ~100 Hz. This makes the activation sparse (i.e., saving energy), but, more importantly, this short-term synaptic dynamics provides unique computational advantages. For instance, short-term depression of synapses (*41*) allows rapid event onset detection, contributing to biological event–based visual processing and detection of temporally coincident events. Short-term facilitation, in its turn, improves the sensor sensitivity in low-light conditions. These properties have been implemented in some of the mixed-signal neuromorphic devices (*15*, *16*) and can be emulated in computationally more flexible digital ones (*10*, *13*) but have not yet been explored in neuromorphic algorithms or applications in robotic tasks. Note that low firing rates of individual neurons do not prevent fast reaction times of neural populations because the first spike can be emitted with a

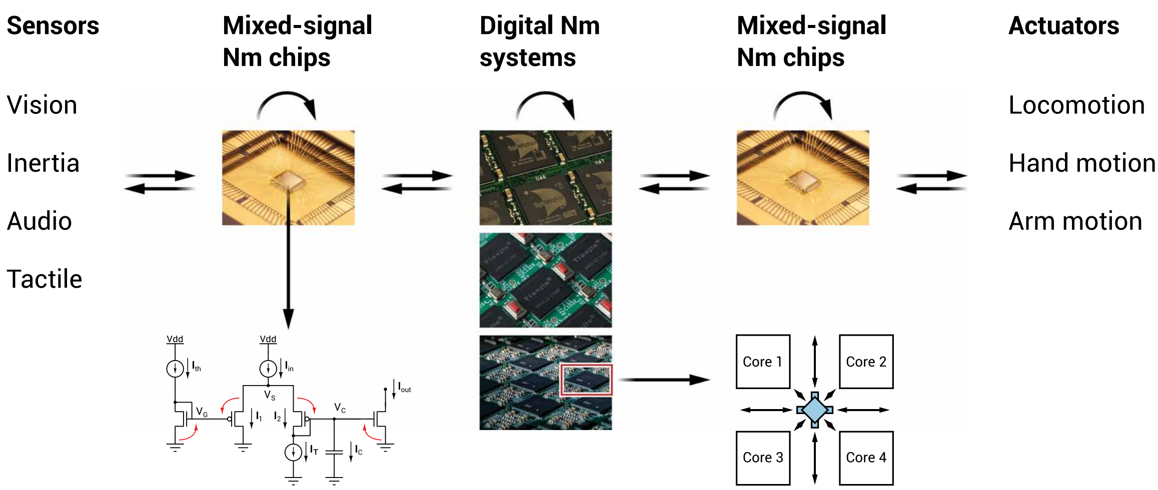

Fig. 1. Neuromorphic computing hardware in robotics. We envision that low-level sensory signal processing can be facilitated by ultralow-power mixed-signal and analog neuromorphic hardware, making sensors in different modalities—visual, auditory, tactile, or proprioceptive—smarter by enabling intelligent computation even before measurements turn into digital representations. The multisensory integration, planning, decision-making, and task-level control can be realized in large-scale neuromorphic devices such as Loihi, SpiNNaker, TrueNorth, or Tianjic chips, to name just a few research devices available today. These devices often comprise multiple computing cores and can host large and heterogeneous neural network architectures. On the motor side, low-power and fast neuromorphic computing could support local reflexes and central pattern generators that simplify the high-level movement control and add the type of embodied intelligence so prominent in the animal motion control. All levels of perception, cognition, and control need to be bidirectionally and efficiently interconnected, forming feedback loops on different time scales, resembling the architecture of biological brains.

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short latency and can have an immediate influence on downstream systems through population effect.

Adaptive spike threshold (*38*, *42*) is another mechanism that is important for signal processing in biological neural networks. In neurons, the voltage threshold, at which a spike is generated, depends on the temporal derivative of the voltage and controls the neuronal integration time window and slope (*43*). Regulation of the temporal dynamics of the raising and decaying part of the spike affects the computational capacity. This, as shown in a recurrent spiking neural network realized with resistive memory circuits, improves classification accuracy and can support, e.g., speech processing (*43*).

Direct one-to-one connections between neurons in biological and neuromorphic neural networks can form feedforward and recurrent connectivity patterns, which are likely sufficient to propagate sensory information, create neural representations, and control movement (*22*). However, context- and task-specific information processing seems to additionally require neuromodulatory transmission, including but not limited to dopamine and serotonin (*44*). Coactivation of the excitatory glutamatergic neurons and dopaminergic neurons, for example, can modulate the sign of synaptic plasticity: whereas glutamate and dopamine in isolation induce synaptic potentiation of the synaptic communication, and when they are coreleased, they induce synaptic depression (*45*). Thanks to the recent exploitation of tunable charge carriers in electronic devices (*45*), the neuromorphic hardware toolbox can be expanded with a new class of synaptic circuits, allowing reinforcement learning mechanisms to be implemented directly in computing devices. Digital neuromorphic devices also support three-factor learning rules and global modulatory signals. Recently, models that make use of astrocytes—non-neuronal cells in the brain—in modulating plasticity have been implemented in the Loihi neuromorphic device (*46*, *47*).

Such neuromodulatory mechanisms are also crucial in memory formation. Biological neural networks store memories transiently. For example, the short-term adaptation of electrochemical dynamics through modulation of neurotransmitter release and receptor de/sensitization provides information storage across pairs of neurons for a few seconds (*41*). Synaptic potentiation and depression, which are commonly implemented through Hebbian learning, realized with different spike timing–dependent plasticity rules, expand the time course to hours and spatial scale to local populations of neurons (*48*, *49*). Longer-term storage solutions require wiring reorganization, i.e., structural plasticity, and various neuromodulators regulate information storage at the network level for shorter periods of time (*24*, *44*, *48*). The transient nature of memory storage does not counteract the permanence of certain memories. Neuromorphic implementation for permanent storage of information could take advantage of information recall and reconsolidation (*50*), possibly during "sleep," similar to active system reconsolidation observed in animal and human brains (*51*).

All these elementary computing capabilities could support the development of neuromorphic robotic architectures, harvesting low-power neural network processing in neuromorphic hardware. Figure 2 shows the analogy between computing hierarchy of biological neural systems and neuromorphic systems, with characteristic dynamics on each level of abstraction. Neuromorphic computing requires understanding of these dynamics and thus computing primitives and algorithms on each level of abstraction.

TOWARD NEUROMORPHIC ROBOTICS

To be successful in real-world tasks, smart robots need to process multisensory signals on different time scales to support sensorimotor loops with different latencies and control rates; interpret complex and dynamic environments based on the sensor signals and memory; plan and execute actions directed at some objects in the environment and avoiding other ones; interact and communicate with humans and other agents; and learn and continually adapt to the changing conditions and contexts. These capabilities will allow robots to collaborate with humans and act in real-world environments that are often complex and ever changing.

Neuromorphic computing systems have a lot of potential for the development of smart robots and embodied AI for robotics. First, they natively support multiple parallel and asynchronous processing streams at very low power, high throughput, and low latency, leaving enough time and energy to perform intelligent computing. Second, they can run neuronal networks with a wide range of topologies, including sparse networks and feedback loops on different spatial and temporal scales, supporting massively parallel distributed algorithms. Last, local always-on plasticity in neuromorphic hardware enables continual learning to shape and adapt neuronal networks using both training data and behavioral experience. Thus, neuromorphic hardware can enable perceptive and cognitive capabilities that are extremely costly in conventional computing hardware. Neuromorphic hardware continues to develop and can be further enriched with the alternative computing principles derived from neuroscientific insights, as briefly, albeit not exhaustively, discussed above. Next, we review some examples of applications of neuromorphic hardware in robotics that have already shown promise.

One of the key tasks in mobile robotics is simultaneous localization and mapping (SLAM). This task requires estimation of the state of a mobile agent—its position and orientation in an environment—based on the available sensor information and motor commands. Most approaches to SLAM are based on the integration of the sensory information with the current state estimate, where uncertainty in the estimate is typically expressed in a probabilistic, e.g., Bayesian, framework (*52*). A biologically inspired version of SLAM, called RatSLAM, approximates the spatial computations of the hippocampal and entorhinal cortex in the rat brain and has shown competitive performance in a real-world map formation task (*53*, *54*). Modern implementations of this neuronal architecture in neuromorphic hardware show that SLAM can be solved efficiently in neuromorphic hardware (*55*–*57*): e.g., 100× lower dynamic power consumption has been shown in Intel's Loihi compared with conventional CPU in a simple proof-of-concept implementation (*36*).

Apart from the state estimation, full SLAM relies on visual place recognition, which helps to localize a "lost" robot or triggers the loop closure events—events when the robot revisits the same place, detects this fact, and uses it to correct the accumulated localization errors. This capability requires storing of visual appearances associated with different

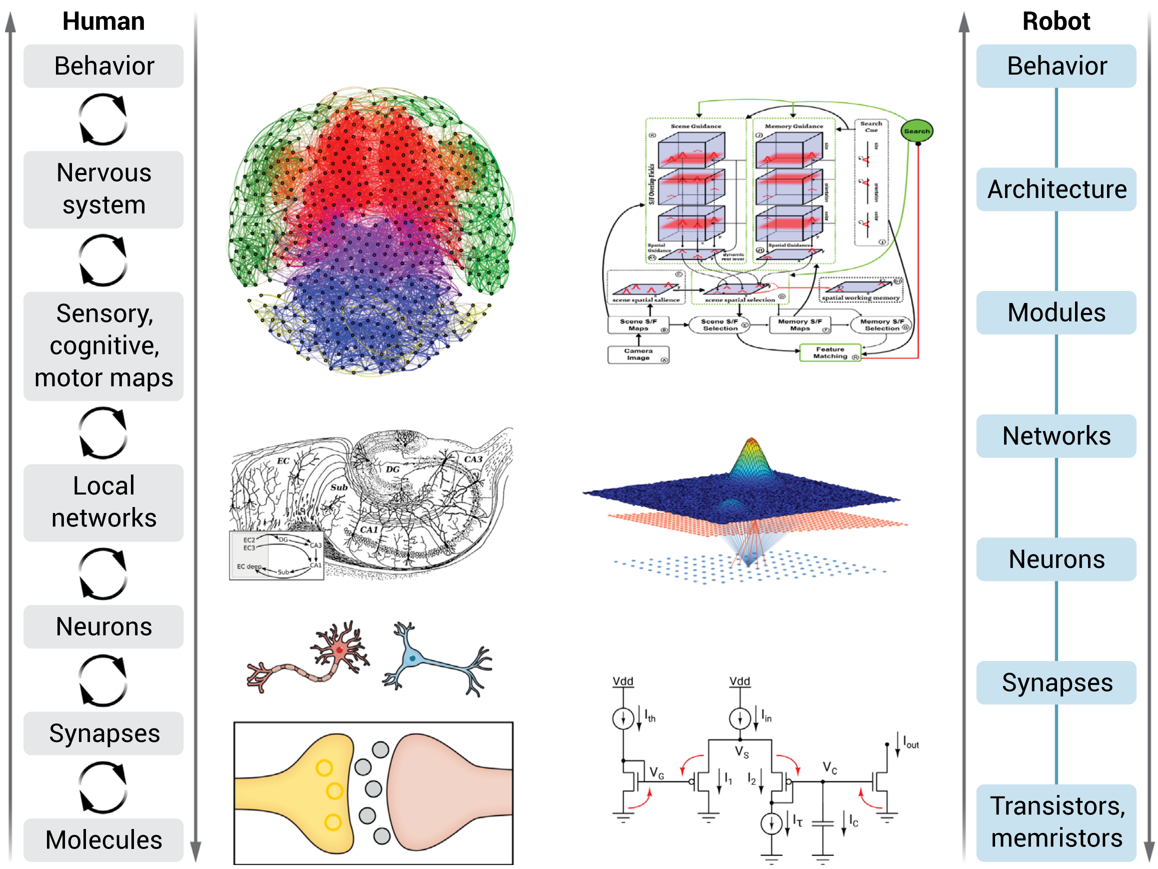

Fig. 2. Principles of information processing in biological networks and in neuromorphic circuits. The signal flow in biological and neuromorphic circuits unfolds on different spatial and temporal scales. A hierarchy of closed-loop control flows can be built both for biological neural systems and neuromorphic systems. In biology, these loops start with molecular dynamics of neurotransmitters, followed by dynamics of neurons and synapses, then local network circuits (e.g., the hippocampal circuits shown here), different sensory-motor cortical maps, ultimately leading to behavior. In a similar fashion, starting with dynamics of individual transistors and simple circuits, dynamics of neurons and synapses can be built, followed by networks, network modules, and whole architectures that can control autonomous behavior of a robot. We need to build theory, computing framework, and algorithmic understanding on these different levels of abstraction.

locations and an ability to retrieve previously stored views based on the current observation. This is a computationally expensive task on a conventional processor. On a neuromorphic device, a search among stored patterns can happen in parallel and be refined over several time steps of recurrent dynamics, showing promise for fast embedded implementation (*58–60*).

Another example of a robotic capability that can be brought to a new level with neuromorphic hardware is fast, online learning of patterns. Although deep learning has shown impressive results in solving image classification tasks on a given dataset (*61*, *62*), the variability of object appearance, camera parameters, and viewpoints in a typical robotic setting (*63*) limits the utilization of large networks pretrained on common image datasets. Neuromorphic hardware platforms support continual learning: The synapses (their weights and delays) in the network can be updated at any time. This property, along with biological learning architectures, could inspire new learning algorithms and network topologies, not relying on slow gradient-based backpropagation, leading to fast learning of visual and other sensory patterns, more suitable for online adaptation and learning in robotic scenarios. Today, examples of workloads with fast learning include online learning of gestures (*63*), learning visual-tactile associations (*64*), one-shot learning of odors (*65*), and fast learning of object views (*66*).

Neuromorphic hardware could also enable performance breakthroughs in motion control. Today, control methods include proportional integral derivative (PID) controllers for systems, in which fast feedback control is possible, and no precise model of the actuator dynamics is needed, as well as model predictive control (MPC) for complex motor plants, for which a precise model is available (*67*). The latter approach achieves impressive results with complex and compliant robots; however, it can be computationally expensive. Neuromorphic hardware has been shown to decrease the computational load in motor control for adaptive PID controllers (*68*, *69*). In MPC, an important component of the controller is a constrained optimization problem solver that finds an optimal command sequence in the current sensed state. Such constrained optimization problems have been shown to run orders of magnitude faster and more efficiently in spiking neural network-on-chip (*12*, *70*, *71*), pointing at another promising application direction for neuromorphic hardware in robotics, possibly also to motion and action planning tasks. Naturally, biologically inspired methods for movement generation, e.g., based on central pattern generators found in spinal cords of many animals, can run efficiently in neuromorphic hardware (*72–75*), whereas cerebellum-inspired models could be used for learning inverse and forward kinematic models (*76*).

Last, one of the missing elements to enable real-world robotics is a link between advanced visual perception and motor control. One of the challenges in this task is the latency of advanced visual processing: Although an image can typically be analyzed within 100 ms, motor control pipelines often run at kilohertz rates and can tolerate delays that are below 10 ms. Neuromorphic computing, in combination with event-based vision, the sensor part of neuromorphic engineering, can help to enable ultrafast vision for control applications (*77*, *78*). Thus, it has been shown that control rates of up to 20 kHz with a delay of less than 5 ms are possible using event-based cameras (*79–81*). The visual processing in this example amounted to tracking a horizon line on a plane in front of a rotating drone; scaling up this neural network to tackle more complex visual tasks is the subject of current research. These more complex tasks could enable fast object detection, tracking, and trajectory prediction; object localization for reaching; or shape estimation for grasping—tasks that would benefit from real-time integration of visual feedback in the control loop. Some examples of efficient control rely on small neural networks, inspired by visual systems of insects, rather than mammals (*82–84*).

This list of examples is certainly not exhaustive—almost every neuromorphic chip has been tested in some robotic tasks. The ones we listed show the promise of this technology by comparing the computing time, power consumption, and accuracy to more conventional approaches. Still, the examples show individual capabilities on fairly simple versions of the tasks. There are several challenges that make progress in the field of neuromorphic robotics difficult: lacking tools for configuring and debugging spiking neural networks; low number of datasets and shared tasks for benchmarking; and missing standards for interfacing to conventional sensors, motors, and computers. These problems are being tackled by the community as the field matures (*85*). The largest challenge and ongoing task for the field of neuromorphic robotics, however, is the development of algorithms that are well suited for neuromorphic hardware—the problem addressed in the next section.

PROGRAMMING NEUROMORPHIC HARDWARE FOR ROBOTS

Similar to conventional computers, neuromorphic hardware requires algorithms to solve practical tasks. These algorithms have a different nature and require a different theory to measure their complexity and performance than algorithms developed for conventional processors. A neuromorphic algorithm is a neural network architecture with a particular connectivity structure, parameters of neurons, synapses, and learning rules that effectively create a dynamical system in the robotic, closed-loop setup. We are not yet in a position to sketch the theory for this algorithmic space, but we can provide some examples of computing elements and principles that are known from biology and might be useful in robotic applications.

The first observation to note about biological brains is how heterogenous they are. Neurons in different brain regions feature distinct internal dynamics and connectivity patterns, facilitating different computations, e.g., the grid cells that contribute to mammalian navigation (*54*, *86*), hippocampal circuits responsible for the formation of episodic memories (*87*), basal ganglia orchestrating activation of discrete actions (*88*), or cerebellar circuits adjusting sensorimotor mappings leading to smooth continuous movement control (*76*), to name just a few examples. Brains of simpler animals, e.g., insects, feature even more special-purpose structures with fascinating behavior and repeatability between individuals (*89*, *90*). Although learning and plasticity play an important role in how the brain processes signals, the network connectivity is largely prearranged for a given set of computational functions, as defined by genetically encoded developmental programs (*91*). From these biological circuits, we could learn about algorithms or network structures that evolved to solve different tasks and thus draw inspiration for new neuromorphic algorithms.

For instance, deep convolutional neural networks were also inspired by the basic feedforward structure of the visual pipeline in mammals. Today, we know more about visual processing in the brain. Sensory input is not just passed through a sequence of layers in the cortex to arrive at a more abstract and invariant representation. Instead, the top-down feedback filters and selectively amplifies different sensor modalities and attributes, often refining representations in multiple recurrent loops (*92*). Behavioral context, task, and previous decisions of the animal all play a role in signals being amplified or attenuated. Throughout the mammalian cortex, well-preserved connectivity between up to six cortical layers seems to implement recurrent local connectivity with important filtering properties. This "canonical circuit" connectivity (*39*, *93*) integrates bottom-up and top-down information in a way that resembles predictive coding and surprise-driven computing models (*94*, *95*). Understanding and modeling such local connectivity patterns can help us develop building blocks for the powerful neuromorphic perception for robots that feature attentional attenuation for efficiency and self-supervised learning for increased autonomy.

Similar principles are observed not only in the visual pipeline but also in other sensory channels such as auditory (*96*), tactile (*39*), olfactory (*97*), or proprioceptive (*98*). Understanding the basic principles of signal processing, transfer, and recovery in these sensorimotor pathways—or, more precisely, loops—will possibly lead to a new generation of sensing technology, e.g., smart electronic skin, chemical sensors, proprioceptive sensing, and also smarter (e.g., active) visual and auditory sensors.

On the actuation side, mechanisms of biological movement generation often lead to power-efficient and safe motor control solutions, which rely on motion primitives or central pattern generators (*72*, *73*, *94*). A detailed understanding of movement planning and control and its link to distal (visual and auditory) and proximal (sense of touch and proprioception) perception is still evolving in neuroscience and could inform future neuromorphic control and actuation systems for autonomous systems and robots.

Theoretical models of adaptive control loops that underlie cognitive brain dynamics could guide development of neuromorphic algorithms in the future (*99*–*101*). Translating these mathematical and conceptual models, or cognitive architectures, into neuronal network language would not only unleash them as a programming framework for neuromorphic hardware but also shed light on the neural basis of behavior and cognition, finally bridging the symbolic and connectionist view on behavior and cognition. First examples of using cognitive architectures to program neuromorphic hardware show how large-scale behavioral models can be implemented and solve different tasks autonomously (*102*–*104*).

Following the example of biology is, of course, not the only path toward "programming" neuromorphic systems in robotic applications. Another avenue for structuring neuronal networks to solve different tasks is to gain inspiration from conventional algorithms, e.g., Kalman filter, Bayesian Fusion, control theory, or decision-making systems. Because the units that perform computation are fundamentally different from conventional computers, we need a different interpretation of these algorithms that do not rely on sequential code, separation of memory and program, or digital numerical variables but instead take advantage of the features of neuromorphic hardware (*12*, *85*).

Another fascinating possibility is to revisit algorithms that one would never dream of efficiently executing on traditional hardware, for example, algorithms for interactive maps (*105*, *106*), factor graphs (*107*), constraint satisfaction solvers (*70*), and other optimization techniques (*108*). There is one theoretical issue to keep in mind when transferring algorithms into the neuromorphic domain. Neuromorphic computing is based on asynchronous signal processing with events, or spikes, triggered by threshold-crossing. On the contrary, at the core of today's information processing theory is the Shannon sampling theory, which relies on the temporally homogeneous sampling of signals. Although having only a minor influence in many cases, in the long run, we need a better understanding and mathematical formulation of metrics in nonhomogeneously sampled signals to build a reliable and precise neuromorphic computing system (*109*).

CONCLUSION

We believe that neuromorphic computing hardware is a milestone in the development of artificially intelligent systems, which makes it possible to follow the footprints of biological perception, movement generation, and cognition in the development of robotic controllers. Neuromorphic hardware has reached a maturity that allows us to use it in practical applications. The missing elements are neural architectures or algorithms for neuromorphic hardware. Developing such architectures will require a better understanding of the algorithmic space that neuromorphic computing substrates enable and facilitate. We have scratched the surface of this algorithmic space with deep and convolutional neural networks, but there is still a lot to learn from the brains and nervous systems that have evolved in the animal kingdom. Insights from models of biological neural systems could drive innovation in neural network architectures, improving flexibility, versatility, and efficiency of artificial neural networks. We hope that this Viewpoint will inspire research and development into neuromorphic algorithms to unfold the true potential of neuronal network–based technology and AI.

REFERENCES AND NOTES

1. I. Goodfellow, Y. Bengio, A. Courville, *Deep Learning* (The MIT Press, 2016).
2. A. I. Karoly, P. Galambos, J. Kuti, I. J. Rudas, Deep learning in robotics: Survey on model structures and training strategies. *IEEE Trans. Syst. Man Cybern. Syst.* **51**, 266–279 (2021).
3. H. A. Pierson, M. S. Gashler, Deep learning in robotics: A review of recent research. *Adv. Robot.* **31**, 821–835 (2017).
4. N. Sünderhauf, O. Brock, W. Scheirer, R. Hadsell, D. Fox, J. Leitner, B. Upcroft, P. Abbeel, W. Burgard, M. Milford, P. Corke, The limits and potentials of deep learning for robotics. *Int. J. Robot. Res.* **37**, 405–420 (2018).
5. J. Lee, J. Hwangbo, L. Wellhausen, V. Koltun, M. Hutter, Learning quadrupedal locomotion over challenging terrain. *Sci. Robot.* **5**, eabc5986 (2020).
6. A. Loquercio, E. Kaufmann, R. Ranftl, M. Müller, V. Koltun, D. Scaramuzza, Learning high-speed flight in the wild. *Sci. Robot.* **6**, eabg5810 (2021).
7. W. S. McCulloch, W. Pitts, A logical calculus of the ideas immanent in nervous activity. *Bull. Math. Biophys.* **5**, 115–133 (1943).
8. G. Indiveri, B. Linares-Barranco, T. J. Hamilton, A. van Schaik, R. Etienne-Cummings, T. Delbruck, S.-C. Liu, P. Dudek, P. Häfliger, S. Renaud, J. Schemmel, G. Cauwenberghs, J. Arthur, K. Hynna, F. Folowosele, S. Saighi, T. Serrano-Gotarredona, J. Wijekoon, Y. Wang, K. Boahen, Neuromorphic silicon neuron circuits. *Front. Neurosci.* **5**, 73 (2011).
9. F. Akopyan, J. Sawada, A. Cassidy, R. Alvarez-Icaza, J. Arthur, P. Merolla, N. Imam, Y. Nakamura, P. Datta, G.-J. Nam, B. Taba, M. Beakes, B. Brezzo, J. B. Kuang, R. Manohar, W. P. Risk, B. Jackson, D. S. Modha, TrueNorth: Design and tool flow of a 65 mW 1 million neuron programmable neurosynaptic chip. *IEEE Trans. Comput.-Aided Des. Integr. Circuits Syst.* **34**, 1537–1557 (2015).
10. M. Davies, N. Srinivasa, T.-H. Lin, G. Chinya, Y. Cao, S. H. Choday, G. Dimou, P. Joshi, N. Imam, S. Jain, Y. Liao, C.-K. Lin, A. Lines, R. Liu, D. Mathaikutty, S. McCoy, A. Paul, J. Tse, G. Venkataramanan, Y.-H. Weng, A. Wild, Y. Yang, H. Wang, Loihi: A neuromorphic manycore processor with on-chip learning. *IEEE Micro.* **38**, 82–99 (2018).
11. S. Furber, Large-scale neuromorphic computing systems. *J. Neural Eng.* **13**, 051001 (2016).
12. M. Davies, A. Wild, G. Orchard, Y. Sandamirskaya, G. A. F. Guerra, P. Joshi, P. Plank, S. R. Risbud, Advancing neuromorphic computing with loihi: A survey of results and outlook. *Proc. IEEE* **109**, 911–934 (2021).
13. S. B. Furber, F. Galluppi, S. Temple, L. A. Plana, The SpiNNaker project. *Proc. IEEE* **102**, 652–665 (2014).
14. C. Mayr, S. Hoeppner, S. Furber, SpiNNaker 2: A 10 million core processor system for brain simulation and machine learning-Keynote presentation, in *Communicating Process Architectures 2017 & 2018* (IOS Press, 2019), pp. 277-280.

15. S. Moradi, N. Qiao, F. Stefanini, G. Indiveri, A scalable multicore architecture with heterogeneous memory structures for dynamic neuromorphic asynchronous processors (DYNAPs). *IEEE Trans. Biomed. Circuits Syst.* **12**, 106–122 (2018).
16. N. Qiao, H. Mostafa, F. Corradi, M. Osswald, F. Stefanini, D. Sumislawska, G. Indiveri, A reconfigurable on-line learning spiking neuromorphic processor comprising 256 neurons and 128K synapses. *Front. Neurosci.* **9**, 141 (2015).
17. J. Schemmel, D. Briiderle, A. Griibl, M. Hock, K. Meier, S. Millner, A wafer-scale neuromorphic hardware system for large-scale neural modeling, in *Proceedings of 2010 IEEE International Symposium on Circuits and Systems* (IEEE, 2010), pp. 1947–1950.
18. B. Rajendran, A. Sebastian, M. Schmuker, N. Srinivasa, E. Eleftheriou, Low-power neuromorphic hardware for signal processing applications: A review of architectural and system-level design approaches. *IEEE Signal Process. Mag.* **36**, 97–110 (2019).
19. G. Indiveri, Y. Sandamirskaya, The importance of space and time for signal processing in neuromorphic agents: the challenge of developing low-power, autonomous agents that interact with the environment. *IEEE Signal Process. Mag.* **36**, 16–28 (2019).
20. J. Joshi, A. C. Parker, T. Celikel, Neuromorphic network implementation of the somatosensory cortex, in *2013 6th International IEEE/EMBS Conference on Neural Engineering (NER)* (IEEE, 2013), pp. 907–910.
21. S. Hughes, T. Celikel, Prominent inhibitory projections guide sensorimotor computation: An invertebrate perspective. *BioEssays News Rev. Mol. Cell. Dev. Biol.* **41**, e1900088 (2019).
22. A. Azarfar, N. Calcini, C. Huang, F. Zeldenrust, T. Celikel, Neural coding: A single neuron's perspective. *Neurosci. Biobehav. Rev.* **94**, 238–247 (2018).
23. M. Schröter, O. Paulsen, E. T. Bullmore, Micro-connectomics: probing the organization of neuronal networks at the cellular scale. *Nat. Rev. Neurosci.* **18**, 131–146 (2017).
24. S. B. Laughlin, T. J. Sejnowski, Communication in neuronal networks. *Science* **301**, 1870–1874 (2003).
25. S.-C. Liu, J. Kramer, G. Indiveri, T. Delbrück, R. Douglas, Eds., in *Analog VLSI: Circuits and Principles* (MIT Press, 2002).
26. C. Bartolozzi, G. Indiveri, Synaptic Dynamics in Analog VLSI. *Neural Comput.* **19**, 2581–2603 (2007).
27. G. Indiveri, E. Chicca, R. Douglas, A VLSI array of low-power spiking neurons and bistable synapses with spike-timing dependent plasticity. *IEEE Trans. Neural Netw.* **17**, 211–221 (2006).
28. K. A. Boahen, Point-to-point connectivity between neuromorphic chips using address events. *IEEE Trans. Circuits Syst. II Analog Digit. Signal Process.* **47**, 416–434 (2000).
29. B. V. Benjamin, P. Gao, E. McQuinn, S. Choudhary, A. R. Chandrasekaran, J.-M. Bussat, R. Alvarez-Icaza, J. V. Arthur, P. A. Merolla, K. Boahen, Neurogrid: A mixed-analog-digital multichip system for large-scale neural simulations. *Proc. IEEE* **102**, 699–716 (2014).
30. A. Grübl, S. Billaudelle, B. Cramer, V. Karasenko, J. Schemmel, Verification and design methods for the brainscales neuromorphic hardware system. *J. Signal Process. Syst.* **92**, 1277–1292 (2020).
31. Y. Stradmann, S. Billaudelle, O. Breitwieser, F. L. Ebert, A. Emmel, D. Husmann, J. Schemmel, Demonstrating analog inference on the brainscaleS-2 mobile system. arXiv: 2103.15960 (2021).
32. J. J. Yang, D. B. Strukov, D. R. Stewart, Memristive devices for computing. *Nat. Nanotechnol.* **8**, 13–24 (2013).
33. E. Chicca, G. Indiveri, R. J. Douglas, An event-based VLSI network of integrate-and-fire neurons. In *2004 IEEE International Symposium on Circuits and Systems (IEEE Cat. No. 04CH37512)* (IEEE, 2004), vol. 5, pp. V-357.
34. J. Pei, L. Deng, S. Song, M. Zhao, Y. Zhang, S. Wu, G. Wang, Z. Zou, Z. Wu, W. He, F. Chen, N. Deng, S. Wu, Y. Wang, Y. Wu, Z. Yang, C. Ma, G. Li, W. Han, H. Li, H. Wu, R. Zhao, Y. Xie, L. Shi, Towards artificial general intelligence with hybrid Tianjic chip architecture. *Nature* **572**, 106–111 (2019).
35. M. Sorbaro, Q. Liu, M. Bortone, S. Sheik, Optimizing the energy consumption of spiking neural networks for neuromorphic applications. *Front. Neurosci.* **14**, 662 (2020).
36. G. Tang, A. Shah, K. P. Michmizos, Spiking neural network on neuromorphic hardware for energy-efficient unidimensional SLAM, in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (IEEE, 2019), pp. 4176–4181.
37. M. B. Martens, T. Celikel, P. H. E. Tiesinga, A developmental switch for hebbian plasticity. *PLoS Comput. Biol.* **11**, e1004386 (2015).
38. C. Huang, A. Resnik, T. Celikel, B. Englitz, Adaptive spike threshold enables robust and temporally precise neuronal encoding. *PLoS Comput. Biol.* **12**, e1004984 (2016).
39. C. Huang, F. Zeldenrust, T. Celikel, "Cortical representation of touch in silico." bioRxiv 371252 [Preprint] (2020).
40. J. O'Brien, Design principles of electrical synaptic plasticity. *Neurosci. Lett.* **695**, 4–11 (2019).
41. W. G. Regehr, Short-term presynaptic plasticity. *Cold Spring Harb. Perspect. Biol.* **4**, a005702 (2012).
42. P. Plank, A. Rao, A. Wild, W. Maass, A long short-term memory for ai applications in spike-based neuromorphic hardware. arXiv:210703992 (2021).
43. A. Shaban, S. S. Bezugam, M. Suri, An adaptive threshold neuron for recurrent spiking neural networks wit nanodevice hardware implementation. *Nat. Commun.* **12**, 4234 (2021).
44. D. Schubert, N. Nadif Kasri, T. Celikel, J. Homberg, Impact of monoaminergic neuromodulators on the development of sensorimotor circuits, in *Sensorimotor Integration in the Whisker System*, P. Krieger, A. Groh, Eds. (Springer, 2015), pp. 243–273.
45. M. Ma, Y. Ni, Z. Chi, W. Meng, H. Yu, J. Gong, H. Wei, H. Han, X. Wang, W. Xu, Multiplexed neurochemical transmission emulated using a dual-excitatory synaptic transistor. *Npj 2D Mater. Appl. Ther.* **5**, 23 (2021).
46. I. Polykretis, G. Tang, K. P. Michmizos, An astrocyte-modulated neuromorphic central pattern generator for hexapod robot locomotion on Intel's Loihi, in *International Conference on Neuromorphic Systems 2020* ACM, (2020) pp. 1–9.
47. G. Tang, I. E. Polykretis, V. A. Ivanov, A. Shah, K. P. Michmizos, Introducing astrocytes on a neuromorphic processor: Synchronization, local plasticity and edge of chaos, in *Proceedings of the 7th Annual Neuro-inspired Computational Elements Workshop* (ACM, 2019) pp. 1–9.
48. Z. Brzosko, S. B. Mierau, O. Paulsen, Neuromodulation of spike-timing-dependent plasticity: Past, present, and future. *Neuron* **103**, 563–581 (2019).
49. T. Celikel, V. A. Szostak, D. E. Feldman, Modulation of spike timing by sensory deprivation during induction of cortical map plasticity. *Nat. Neurosci.* **7**, 534–541 (2004).
50. S. McKenzie, H. Eichenbaum, Consolidation and reconsolidation: two lives of memories? *Neuron* **71**, 224–233 (2011).
51. J. G. Klinzing, N. Niethard, J. Born, Mechanisms of systems memory consolidation during sleep. *Nat. Neurosci.* **22**, 1598–1610 (2019).
52. S. Thrun, in *Robotics and Cognitive Approaches to Spatial Mapping*, M. E. Jefferies, W.-K. Yeap, Eds. (Springer, 2008), pp. 13–41.
53. M. J. Milford, G. F. Wyeth, D. Prasser, RatSLAM: A hippocampal model for simultaneous localization and mapping, in *IEEE International Conference on Robotics and Automation* (IEEE, 2004), pp. 403–408.
54. F. Yu, J. Shang, Y. Hu, M. Milford, NeuroSLAM: A brain-inspired SLAM system for 3D environments. *Biol. Cybern.* **113**, 515–545 (2019).
55. R. Kreiser, A. Renner, Y. Sandamirskaya, P. Pienroj, Pose estimation and map formation with spiking neural networks: Towards neuromorphic SLAM, in *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (IEEE, 2018), pp. 2159–2166.
56. R. Kreiser, A. Renner, V. R. C. Leite, B. Serhan, C. Bartolozzi, A. Glover, Y. Sandamirskaya, An on-chip spiking neural network for estimation of the head pose of the iCub robot. *Front. Neurosci.* **14**, 551 (2020).
57. R. Kreiser, M. Cartiglia, J. N. P. Martel, J. Conradt, Y. Sandamirskaya, in *2018 IEEE International Symposium on Circuits and Systems (ISCAS)* (IEEE, 2018), pp. 1–5.
58. E. P. Frady, G. Orchard, D. Florey, N. Imam, R. Liu, J. Mishra, J. Tse, A. Wild, F. T. Sommer, M. Davies, in *Proceedings of the Neuro-inspired Computational Elements Workshop* (ACM, 2020), pp. 1–10.
59. S. Garg, T. Fischer, M. Milford, Where is your place, Visual place recognition? arXiv:210306443 (2021).
60. T. Fischer, M. Milford, Event-based visual place recognition with ensembles of temporal windows. *IEEE Robot. Autom. Lett.* **5**, 6924–6931 (2020).
61. S. B. Shrestha, G. Orchard, SLAYER: Spike layer error reassignment in time. arXiv:181008646 (2018).
62. E. O. Neftci, H. Mostafa, F. Zenke, Surrogate gradient learning in spiking neural networks: Bringing the power of gradient-based optimization to spiking neural networks. *IEEE Signal Process. Mag.* **36**, 51–63 (2019).
63. G. Pasquale, C. Ciliberto, F. Odone, L. Rosasco, L. Natale, Are we done with object recognition? The iCub robot's perspective. *Robot. Auton. Syst.* **112**, 260–281 (2019).
64. K. Stewart, G. Orchard, S. B. Shrestha, E. Neftci, Online few-shot gesture learning on a neuromorphic processor. *IEEE J. Emerg. Sel. Top. Circuits Syst.* **10**, 512–521 (2020).
65. T. Taunyazov, W. Sng, H. H. See, B. Lim, J. Kuan, A. F. Ansari, B. C. K. Tee, H. Soh, Event-driven visual-tactile sensing and learning for robots. arXiv:200907083 (2020).
66. S. Baumgartner, A. Renner, R. Kreiser, D. Liang, G. Indiveri, Y. Sandamirskaya, Visual pattern recognition with on on-chip learning: Towards a fully neuromorphic approach, in *2020 IEEE International Symposium on Circuits and Systems (ISCAS)* (IEEE, 2020), pp. 1–5.
67. R. Grandia, F. Farshidian, R. Ranftl, M. Hutter, Visual pattern recognition with on on-chip learning: Towards a fully neuromorphic approach, in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (IEEE, 2019), pp. 4730–4737.
68. T. DeWolf, P. Jaworski, C. Eliasmith, Nengo and low-power ai hardware for robust, embedded neurorobotics. *Front. Neurorobot.* **14**, 568359 (2020).
69. Y. Zaidel, A. Shalumov, A. Volinski, L. Supic, E. Ezra Tsur, Neuromorphic NEF-based inverse kinematics and PID control. *Front. Neurorobot.* **15**, 631159 (2021).
70. G. A. Fonseca Guerra, S. B. Furber, Using stochastic spiking neural networks on SpiNNaker to solve constraint satisfaction problems. *Front. Neurosci.* **11**, 714 (2017).
71. C. Yakopcic, N. Rahman, T. Atahary, T. M. Taha, S. Douglass, Solving constraint satisfaction problems using the loihi spiking neuromorphic processor, in *2020 Design, Automation & Test in Europe Conference & Exhibition (DATE)* (IEEE, 2020), pp. 1079–1084.

72. A. J. Ijspeert, J. Nakanishi, H. Hoffmann, P. Pastor, S. Schaal, Dynamical movement primitives: Learning attractor models for motor behaviors. *Neural Comput.* **25**, 328–373 (2013).
73. A. J. Ijspeert, Central pattern generators for locomotion control in animals and robots: A review. *Neural Netw.* **21**, 642–653 (2008).
74. D. Gutierrez-Galan, J. P. Dominguez-Morales, F. Perez-Peña, A. Jimenez-Fernandez, A. Linares-Barranco, Neuropod: A real-time neuromorphic spiking CPG applied to robotics. *Neurocomputing* **381**, 10–19 (2020).
75. I. Polykretis, G. Tang, K. P. Michmizos, An astrocyte-modulated neuromorphic central pattern generator for hexapod robot locomotion on Intel's Loihi, in *International Conference on Neuromorphic Systems 2020* (ACM, 2020), pp. 1–9.
76. P. A. Bogdan, B. Marcinnò, C. Casellato, S. Casali, A. G. D. Rowley, M. Hopkins, F. Leporati, E. D'Angelo, O. Rhodes, Towards a bio-inspired real-time neuromorphic cerebellum. *Front. Cell. Neurosci.* **15**, 622870 (2021).
77. G. Gallego, T. Delbruck, G. M. Orchard, C. Bartolozzi, B. Taba, A. Censi, S. Leutenegger, A. Davison, J. Conradt, K. Daniilidis, D. Scaramuzza, Event-based vision: A survey. *IEEE Trans. Pattern Anal. Mach. Intell.* **44**, 154–180 (2022).
78. P. P. Parlevliet, A. Kanaev, C. P. Hung, A. Schweiger, F. D. Gregory, R. Benosman, G. C. H. E. de Croon, Y. Gutfreund, C.-C. Lo, C. F. Moss, Autonomous flying with neuromorphic sensing. *Front. Neurosci.* **15**, 672161 (2021).
79. R. Stagsted, A. Vitale, J. Binz, A. Renner, L. Bonde Larsen, Y. Sandamirskaya, Towards neuromorphic control: A spiking neural network based PID controller for UAV, in *Robotics: Science and Systems XVI* (Robotics: Science and Systems Foundation, 2020).
80. R. K. Stagsted, A. Vitale, A. Renner, L. B. Larsen, A. L. Christensen, Y. Sandamirskaya, Event-based PID controller fully realized in neuromorphic hardware: A one DoF study, in *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (IEEE, 2020), pp. 10939–10944.
81. A. Vitale, A. Renner, C. Nauer, D. Scaramuzza, Y. Sandamirskaya, Event-driven Vision and Control for UAVs on a Neuromorphic Chip. arXiv:210803694 (2021).
82. J. Dupeyroux, J. Hagenaars, F. Paredes-Vallés, G. de Croon, Neuromorphic control for optic-flow-based landings of MAVs using the Loihi processor, in *2021 IEEE International Conference on Robotics and Automation* (IEEE, 2021) pp. 96–102.
83. L. Salt, D. Howard, G. Indiveri, Y. Sandamirskaya, Parameter optimization and learning in a spiking neural network for UAV obstacle avoidance targeting neuromorphic processors. *IEEE Trans. Neural Netw. Learn. Syst.* **31**, 3305–3318 (2020).
84. M. B. Milde, O. J. Bertrand, H. Ramachandran, M. Egelhaaf, E. Chicca, Spiking elementary motion detector in neuromorphic systems. *Neural Comput.* **30**, 2384–2417 (2018).
85. D. V. Christensen, R. Dittmann, B. Linares-Barranco, A. Sebastian, M. L. Gallo, A. Redaelli, S. Slesazeck, T. Mikolajick, S. Spiga, S. Menzel, I. Valov, G. Milano, C. Ricciardi, S.-J. Liang, F. Miao, M. Lanza, T. J. Quill, S. T. Keene, A. Salleo, J. Grollier, D. Marković, A. Mizrahi, P. Yao, J. J. Yang, G. Indiveri, J. P. Strachan, S. Datta, E. Vianello, A. Valentian, J. Feldmann, X. Li, W. H. P. Pernice, H. Bhaskaran, E. Neftci, S. Ramaswamy, J. Tapson, F. Scherr, W. Maass, P. Panda, Y. Kim, G. Tanaka, S. Thorpe, C. Bartolozzi, T. A. Cleland, C. Posch, S.-C. Liu, A. N. Mazumder, M. Hosseini, T. Mohsenin, E. Donati, S. Tolu, R. Galeazzi, M. E. Christensen, S. Holm, D. Ielmini, N. Pryds, 2022 Roadmap on neuromorphic computing and engineering. arXiv 210505956 (2021).
86. T. Hafting, M. Fyhn, S. Molden, M.-B. Moser, E. I. Moser, Microstructure of a spatial map in the entorhinal cortex. *Nature* **436**, 801–806 (2005).
87. N. Burgess, E. A. Maguire, J. O'Keefe, The human hippocampus and spatial and episodic memory. *Neuron* **35**, 625–641 (2002).
88. A. M. Graybiel, T. Aosaki, A. W. Flaherty, M. Kimura, The basal ganglia and adaptive motor control. *Science* **265**, 1826–1831 (1994).
89. F. C. Rind, Motion detectors in the locust visual system: From biology to robot sensors. *Microsc. Res. Tech.* **56**, 256–269 (2002).
90. D. Turner-Evans, S. Wegener, H. Rouault, R. Franconville, T. Wolff, J. D. Seelig, S. Druckmann, V. Jayaraman, Angular velocity integration in a fly heading circuit. *eLife* **6**, e23496 (2017).
91. A. Simi, M. Studer, Developmental genetic programs and activity-dependent mechanisms instruct neocortical area mapping. *Curr. Opin. Neurobiol.* **53**, 96–102 (2018).
92. L. G. Ungerleider, J. V. Haxby, "What" and "where" in the human brain. *Curr. Opin. Neurobiol.* **4**, 157–165 (1994).
93. R. J. Douglas, K. A. C. Martin, D. Whitteridge, A canonical microcircuit for neocortex. *Neural Comput.* **1**, 480–488 (1989).
94. M. W. Spratling, A review of predictive coding algorithms. *Brain Cogn.* **112**, 92–97 (2017).
95. V. Liakoni, A. Modirshanechi, W. Gerstner, J. Brea, Learning in volatile environments with the bayes factor surprise. *Neural Comput.* **33**, 269–340 (2021).
96. S. Shamma, J. Fritz, Adaptive auditory computations. *Curr. Opin. Neurobiol.* **25**, 164–168 (2014).
97. M. Wachowiak, All in a sniff: Olfaction as a model for active sensing. *Neuron* **71**, 962–973 (2011).
98. J. L. Chen, D. J. Margolis, A. Stankov, L. T. Sumanovski, B. L. Schneider, F. Helmchen, Pathway-specific reorganization of projection neurons in somatosensory cortex during learning. *Nat. Neurosci.* **18**, 1101–1108 (2015).
99. P. F. Verschure, Distributed adaptive control: A theory of the mind, brain, body nexus. *Biol. Inspired Cogn. Archit.* **1**, 55–72 (2012).
100. F. E. Ritter, F. Tehranchi, J. D. Oury, ACT-R: A cognitive architecture for modeling cognition. *Wiley Interdiscip. Rev. Cogn. Sci.* **10**, e1488 (2019).
101. S. Grossberg, Toward autonomous adaptive intelligence: Building upon neural models of how brains make minds, in *IEEE Transactions on Systems, Man, and Cybernetics: Systems* (IEEE, 2021), vol. 51, pp. 51–75.
102. S. V. Adams, A. D. Rast, C. Patterson, F. Galluppi, K. Brohan, J. A. Pérez-Carrasco, A. Cangelosi, Towards real-world neurorobotics: Integrated neuromorphic visual attention, in *International Conference on Neural Information Processing* (Springer, 2014) pp. 563–570.
103. S. Yang, J. Wang, X. Hao, H. Li, X. Wei, B. Deng, K. A. Loparo, BiCoSS: Toward large-scale cognition brain with multigranular neuromorphic architecture. *IEEE Trans. Neural Netw. Learn. Syst.* 1–15 (2021).
104. F. X. Choo, Spaun 2.0: Extending the world's largest functional brain model. (2018).
105. J. N. P. Martel, thesis, ETH Zurich (2019); www.research-collection.ethz.ch/handle/20.500.11850/362900.
106. M. Cook, L. Gugelmann, F. Jug, C. Krautz, A. Steger, Interacting maps for fast visual interpretation, in *The 2011 International Joint Conference on Neural Networks* (IEEE, 2011), pp. 770–776.
107. P. U. Diehl, J. Martel, J. Buhmann, M. Cook, Factorized computation: What the Neocortex can tell us about the future of computing. *Front. Comput. Neurosci.* **12**, 54 (2018).
108. H. Antil, D. P. Kouri, M.-D. Lacasse, D. Ridzal, The IMA volumes in mathematics and its applications, in *Frontiers in PDE-Constrained Optimization* (Springer, ed. 1, 2018), pp. 903.
109. M. Pelillo, E. R. Hancock, in *Similarity-Based Pattern Recognition* (Springer, 2011).

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