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Fluid learning: Nanofluidic device platforms for neuromorphic ionic computing

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Fluid learning:

Mimicking brain computing with neuromorphic nanofluidic devices

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ABSTRACT:

Relentlessly rising energy demands in computing call for rethinking hardware paradigms with energy efficiency in mind. Nature's example—the brain—raises the question: How can these natural computers achieve remarkable feats with minimal energy compared to supercomputers? Neuromorphic computing mimics the brain's principles, but current neuromorphic concepts using electronic components face scalability and their own power consumption challenges. A potentially revolutionary approach is emerging: computing with ion transport in water through nanochannels. This field offers energy-efficient possibilities by imitating brain-like information processing with different types of ions as carriers. The goal is to converge advanced nanoscale architectures with brain-inspired efficiency, heralding a new era of computing.

A seemingly impossible task caught the attention of the entire world in 2011. Ken Jennings and Brad Rutter, two formidable champions, and Watson, an unexpected foe, squared off on the Jeopardy quiz show, known for testing human knowledge and agility. Watson was not a human candidate like Jennings and Rutter; instead, he was an IBM machine. Amazingly, Watson prevailed, demonstrating the vast potential of computing and artificial intelligence (AI). This victory, however, came at a high cost—Watson used at least a thousand times more energy than its human rivals.

This incident is a sobering reminder of the rising energy requirements of contemporary computing systems. Our insatiable appetite for processing capacity has caused environmental sustainability and energy consumption to come under scrutiny as society grows more and more

dependent on technology. Rethinking computing paradigms with energy efficiency at their core is essential to overcome this problem.

Nature provides us with an intriguing example—our own brains. While a comparison between the human brain and today's computers may seem audacious, it sheds light on a fundamental question: How can the brain achieve remarkable cognitive feats while drawing on a fraction of the energy consumed by state-of-the-art supercomputers?

Scientists and technologists have set out on a mission to create neuromorphic computing [1], a paradigm that imitates the computational principles of the brain, in response to this biological miracle [2]. While not often highlighted as a reason for the brain's unmatched energy efficiency, it can be partly attributed to our capacity for information transmission and processing via the carefully controlled interaction of different ions and molecules. Current neuromorphic computing concepts, however, have not exploited this principle. Moreover, the majority of current technologies rely on conventional electronic components, which presents fundamental problems with scalability, power consumption, connectivity, and computational complexity [3].

A potentially revolutionary approach—computing utilizing ion transport in water through nanochannels—offers a route around these obstacles and a path to realize the full potential of neuromorphic computing [4]. By harnessing the power of fluidic systems and nanotechnology, researchers are beginning to explore new frontiers in computing, where ions serve as carriers of information, akin to (ions and) neurotransmitters in the brain. This emerging field presents an exciting opportunity to transform computing architecture and design extremely energy-efficient systems with neuromorphic concepts at their core. Here, we highlight the prospects and challenges of utilizing ion transport through nanochannels as a pathway to energy-efficient computing. We envision a future where advanced nanoscale architectures converge with the efficiency of the human brain, heralding a new era of energy-efficient and brain-inspired computing.

Fundamentally, the energy cost of irreversible computing is given by the Landauer bound of ($k_B T$ ln 2/bit), where k_B is Boltzmann's constant and T is temperature [5]. For comparison, a modern state-of-the-art GPU unit (NVIDIA A100) uses about 1,200 fJ/bit, which is approximately nine orders of magnitude higher than the Landauer limit. In contrast, neurons use just 0.1 fJ/spike, making the brain at least 10,000 times more energy-efficient, even before counting the additional efficiencies associated with multiple information carrier computing.

When we envision computing that mimics information handling in a human brain, we must consider devices that not only can store and process information, but also implement core-level learning behaviors analogous to short-term and long-term potentiation and synaptic plasticity (Fig. 1). Ideally, all these capabilities will be localized on the same devices, avoiding the costly von Neumann bottleneck associated with information shutting between memory and a CPU.

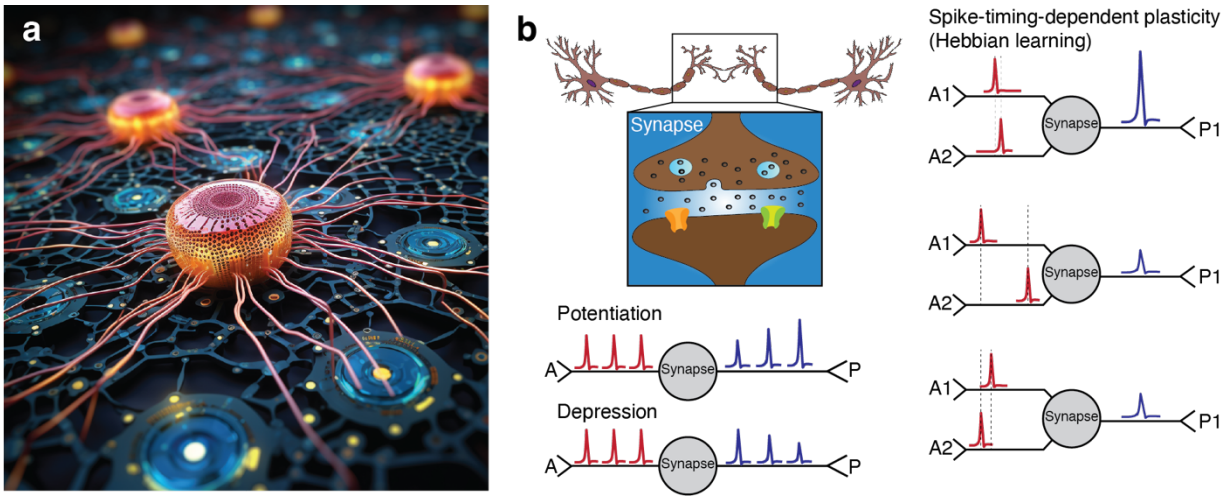

Figure 1. Neuromorphic computing. a. A graphic produced by an AI-driven image generation engine (Mindjourney) in response to a "*Neuromorphic nanofluidic computing*" prompt. **b**. Schematics of a biological synapse illustrating some of the key neuronal functionality that enables information processing and learning in the brain.

What kind of devices and material platforms can deliver on this vision? In the brain, neurons propagate information and communicate with each other through synaptic junctions that can stimulate or inhibit the activity of the downstream (post-synaptic) neuron. Neural networks, which power most modern AI, simulate synaptic function by passing the signal through multiple junctions that have adjustable weights that determine the signal path through the network or relative contributions of the network elements to the final output [6]. The device that has emerged as a fundamental unit implementing this behavior is a memristor [6-8], a device that can assume different resistive states depending on its applied voltage history and is distinguished by its single (or multiple) pinched-loop hysteretic IV (ion current-voltage) curve (Fig. 2). A voltage pulse or a series of voltage pulses applied to a memristor can increase (or decrease) its conductance, affecting the subsequent signal transmission, and thus giving the device "memory" of its stimulation history and allowing it to implement basic neuromorphic functionality similar to what we depict in Fig 1b. For example, a train of voltage pulses that pushes the memristor into progressively higher conductance states simulates positive potentiation behavior. If two input pulses are close enough in the time domain, they can combine to push the memristor to a higher conductance state, delivering spike-timing-dependent plasticity functionality.

Memristors were theoretically proposed by Chua [7] and then first realized in solid-state electronic devices [9]. Subsequently, many example of neuromorphic computing circuits based on solid-state electronic memristors arrays have emerged [3, 8, 10]. Recently we also have started to see ion-based memristor implementations. Nanofluidic memristor behavior was first demonstrated by Siwy and co-workers in 2011 in a hydrophobic conical nanopore [11]; Wang et

al. also observed memristive behavior in 2012 using ion transport in a charged conical nanopore [12]. Subsequently, researchers have reported nanofluidic memristor implementations based on a number of nanopore- and nanochannel-based platforms. In particular, two such platforms, an activated carbon nanochannel memristor [13] and a polymer-grafted nanopipette memristor [14], have demonstrated primitive examples of short-term potentiation and spike-timing-dependent plasticity (Hebbian learning), paving the way for future nanofluidic computing operations.

Several physical phenomena are associated with creating the temporary ion accumulation and depletion conditions that represent the conductance ON and OFF branches of the memristive curve and are fundamental to neuromorphic behaviors observed in several types of devices (Fig. 2). Strong size asymmetry between the two entrances can lead to hysteresis as the voltage sweep driving ions in and out of the channel switches direction (Fig. 2a). Wang et al. showed that the ion redistribution within the electric double layer of a conical nanopore can lead to pinched-hysteretic loops [12]. Their work indicated that when the ions have to pass through a nanometer-scale channel, the hysteresis timescale could extend into the millisecond time range—offering opportunities to potentially exploit the phenomenon for computing. Ionic concentration polarization, induced by permselective nanochannels in which one kind of ionic species is preferentially transported over another, can cause memristive behavior when the increase in driving voltage leads to ion current saturation (Fig. 2b) [15]. Ionic band gaps that arise either as a result of ion-pair association from the Wien effect [13] or spatial resistance [16] in the nanochannels can also produce hysteresis loops (Fig. 2c). Note that these three mechanisms produce different directions of IV hysteresis loops and are distinguished by rather different-looking conductance-vs.-voltage (G-V) characteristics. There is also a possibility of observing transitions between these mechanisms where hysteresis loops form multiple crossing points. For example, as the driving voltage increases, the hysteresis loop may transition from the entrance-asymmetry-induced mechanism to concentration-polarization-dominated behavior (Fig. 2d).

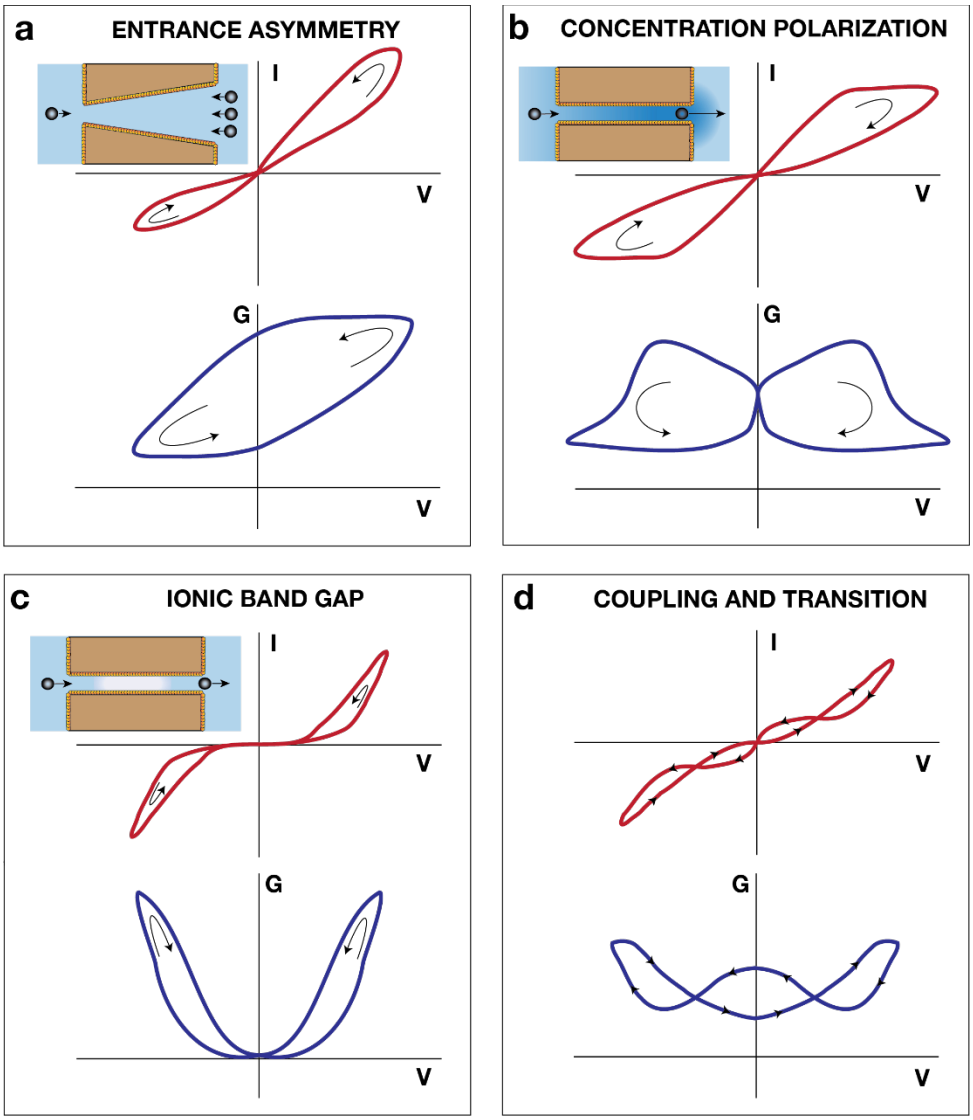

Figure 2. Nanofluidic memristors. Current-voltage (top) and conductance-voltage (bottom) characteristics of different memristive ion channel exploiting (**a**) spatial asymmetry, (**b**) concentration polarization, and (**c**) ionic band gap mechanisms, as well as (**d**) the potential coupling and transition between those mechanisms. Insets in *a-c* illustrate the mechanisms responsible for hysteresis creation.

While the emergence of hysteretic behavior in nanofluidic systems is not surprising or even unexpected, a second category of physical processes is responsible for pushing the timescale of this hysteresis into the millisecond-to-minute range that enables experimental realization of neuromorphic synaptic behavior. One common feature is a high degree of spatial confinement, which enhances the role of surface processes and ion interactions, leading to additional non-linear ion transport effects [17, 18]. Most of the nanofluidic memristive devices described in the literature tend to operate in the high Dukhin number regime where surface transport is prevalent (Dukhin number, *Du*, is a dimensionless parameter derived from the ratio of surface conductance to bulk conductance). Because significant surface conductance almost always requires the presence of surface charge, memristive behavior is also associated with non-zero

permselectivity of a channel. Finally, adsorption-desorption processes at the channel surface can combine with strong spatial confinement to define the kinetics of establishing the ON and OFF states; for example surface equilibrium in narrow activated graphite channels pushes the memory (hysteresis) timescale of those devices into very long (hundreds of seconds) timescales [13].

It is important to note that all these mechanisms can combine to produce and enhance the hysteretic behavior. Confinement often leads to a significant overlap of the Debye layers in a nanofluidic channel, enhanced channel permselectivity, and a significant contribution from surface transport to the overall channel conductance. The extremely high surface-to-volume ratios associated with nanochannels also enhance the contribution of the adsorption-desorption processes to the overall dynamics of charge carriers in the channel.

Even a brief survey of reported synaptic-mimicking devices indicates the enormous potential that these nanofluidic platforms have for energy-efficient neuromorphic ionic computing. These devices represent early prototypes, but they already are showing promising energy consumption. For example, the nanopipette-based ionic memristor power consumption is on the order of 600 fJ/spike, which is several orders of magnitude lower than many existing solid-state electronic neuromorphic devices [14, 19]. However, this energy is still several orders of magnitude higher than the energy consumed by a biological neuron [20]. The performance gap is even wider when we consider the functionality of the device. The demonstration of Hebbian learning, an example of spike-timing-dependent plasticity behavior, in a nanofluidic device was an important milestone; however, the ability of the nanofluidic circuit to discriminate the temporal proximity of the incoming pulses still remains worse than biological systems (Fig. 3). One of the reasons for this discrepancy is that biological systems have evolved a mechanism where a secondary messaging cascade can be triggered by the modulatory cell to enhance the postsynaptic response [21], whereas nanofluidic synapses rely on the additive interaction of the presynaptic and modulatory inputs.

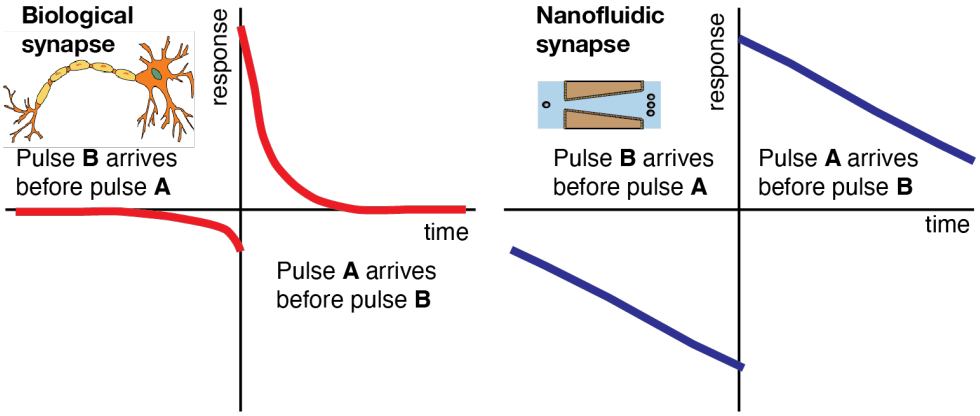

Figure 3. Hebbian learning performance. Conductance response as a function of relative spike timing for a biological synapse (left) and a nanofluidic synapse (right). More abrupt decay of the conductance change indicates better proximity discrimination.

Further advances in neuromorphic ionic computing will require us to tackle several outstanding sets of issues. We need a better understanding of the fundamental mechanisms associated with the ionic memory effects in these devices. For example, while some simulation and modeling papers of neuromorphic ionic device behavior have started to appear [22], it is not clear how the channel size, geometry, and other properties (e.g., surface charge) influence the memory timescale and hysteresis magnitude. In some of the existing examples, hysteresis was observed only under high applied bias; extending ionic memory behavior into lower-voltage regimes would improve energy efficiency tremendously. Another challenge is associated with scalability and interconnectivity of these devices. Extending beyond isolated devices, the development of compact interconnected circuits comprising large numbers of elements would require architectures that can deliver significant interconnectivity in a small volume. Another tantalizing possibility would be to implement these architectures in biocompatible or even implantable form where they could be autonomously powered by the body and provide direct integration with biological signaling and regulatory pathways.

We can also learn from and adapt some of the device functionality that powers solid-state neuromorphic computing, in particular those devices that enable direct on-chip machine learning [23]. Such cross-pollination could accelerate progress in the field and help to develop more robust and efficient ionic device architectures. For example, mixed ionic-electronic conductors (MIECs) [24] have found widespread applications as bioelectronic device platforms [25]. Finally, we need to start developing device platforms for “multi-color” computing that use several types of ionic carriers to expand the information processing capacity of a given channel. For example, the state of the system with two carriers can be “A NOT B”, “B NOT A”, “A AND B”, or “A NOR B”; this is in contrast to a traditional logic system where it is simply ON or OFF (“A” or “NOT A”). Expanding to three or more carriers would represent a further substantial jump in possible states. Achieving this capability will, among other challenges, require development of ion-specific readouts compatible with scaled-up nanofluidic device platforms.

In the pursuit of energy-efficient computing, the exploration of ion transport through nanochannels has opened a new realm of possibilities that could deliver capabilities complementary to the current solid-state device-based computing. While the vision of true ionic computing technology may still be on the horizon, the prospect of harnessing the brain’s efficiency through nanofluidics is tantalizing. By embracing interdisciplinary collaboration, pushing the boundaries of scientific understanding, and navigating the intricacies of engineering and design, we can pave the way for a future where energy-efficient, brain-inspired computing systems become a reality.

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