Emerging materials in neuromorphic computing: Guest editorial

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I. INTRODUCTION

For more than five decades, the flexibility of the von Neumann architecture—in which data from discrete *memory units* arrive at dedicated *compute units* as both *operations* and *operands*—has driven exponential improvements in system performance. These computing systems require large amounts of data to be shuttled back and forth at high speeds during the execution of computational tasks. However, as device scaling has slowed due to power and voltage considerations, the time and energy spent transporting data across the so-called "von Neumann bottleneck" between memory and compute units have become problematic. These performance bottlenecks and significant area/power inefficiencies are particularly inescapable for data-centric applications, such as real-time image recognition and natural language processing, where the state-of-the-art von Neumann systems work hard to match the performance of an average human.

We are on the cusp of a revolution in artificial intelligence (AI) and cognitive computing, with algorithmic advances that have allowed Deep Neural Networks (DNNs) to approach or even surpass the performance of humans on many tasks such as pattern-recognition, game-playing, machine translation, and more. However, the computers that run today's AI algorithms are based on the von Neumann architecture, which means that these machines are many orders of magnitude less energy-efficient than the human brain even as they pass the brain in speed or approach it in accuracy. Thus, it is becoming increasingly clear that, to build efficient cognitive computers, we need to transition to novel architectures where memory and processing are better collocated.[1,2]

The human brain suggests an intriguing non-von Neumann computing paradigm for future computing systems, referred to as either brain-inspired or neuromorphic computing. The brain is characterized by its massively parallel architecture connecting myriad low-power computing elements (neurons) and adaptive memory elements (synapses). It is natural to look to the human brain for inspiration since it is a remarkable engine of cognition that performs computations on the order of peta-ops per joule. Since the brain can outperform modern processors on many tasks involving unstructured data classification and pattern recognition, it provides an "existence proof" for an ultralow power cognitive computer.

Unfortunately, we are still quite far from attaining a comprehensive understanding of how the brain computes. However, we have uncovered certain salient features of this computing system such as the collocation of memory and processing, a computing fabric comprising large-scale networks of neurons and plastic synapses, and spike-based communication and processing of information. Early studies of the brain led to the creation of artificial neural networks. These evolved over many decades into the DNNs responsible for the current AI revolution behind recent breakthroughs in image classification, speech recognition, machine translation, customer prediction, fraud detection, game-playing, and many other commercially relevant applications. Based on these insights, researchers have begun to envision neuromorphic computing systems at multiple levels of inspiration or abstraction.

In the brain, memory and processing are highly entwined. Hence, the memory unit can be expected to play a key role in brain-inspired computing systems. The scaling of dense nonvolatile memory (NVM) crossbar arrays to few-nanometer critical dimensions has been recognized as one path to build computing systems that can mimic the massive parallelism and low-power operation found in the human brain. The human brain has a high degree of connectivity, with any given neuron having as many as 10 000 inputs from other neurons. Dense arrays of NVM elements provide an opportunity to emulate this connectivity in hardware if various engineering difficulties can be overcome. In particular, very high-density, low-power, variable-state, programmable, and nonvolatile memory devices could play a central role.

II. SPECIAL ISSUE

In this context of neuromorphic computing as a promising area of research for future, energy-efficient computing systems, we organized the present Special Issue in *APL Materials* entitled "Emerging Materials in Neuromorphic Computing."

This special issue provides a comprehensive overview on emerging materials at the active frontier of neuromorphic computing. We considered new materials and new uses for established materials, within the context of brain-inspired computing algorithms, ranging from spiking networks to oscillator networks to reservoir computing to deep neural networks. We sought out the interdisciplinary perspective which could integrate materials science, physics, chemistry, computer science, and engineering. The selected articles give a state-of-the-art overview of the progress over the past few years in this topic area.

Many of these articles address resistive switching materials for neuromorphic computing, including devices based on

- phase-change memory,[3,4]
- memristive oxide-filament resistive devices,[5–9]
- electrochemical metal-filament devices,[10,11]
- ferroelectric[12] and organic ferroelectric devices,[13]
- nonfilamentary RRAM materials,[14–16] and
- topological insulator materials.[17]

Several papers studied the interplay between memristor device characteristics and neuromorphic applications.[8,18,19] Other papers focused on photonic applications relevant to neuromorphic computing.[3,9,20,21] Finally, several papers addressed the stochastic operation of devices for the novel synaptic and/or neuronal behavior[6,11,14] to enable stochastic learning algorithms.

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We hope this Special Topic will be relevant and interesting for researchers both in and outside the field.

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