Neuromorphic Computing: History, Current Status, and Future

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Summary. This abstract proposes a presentation on the history, current status, and potential future of the neuromorphic field at large, aimed at supporting a combined understanding of the field's past, present, and possible future as it enters a critical phase of development. The proposed presentation begins with a review of the issues facing standard computing hardware and then proceeds to discuss the principle theory and key technologies under development in the neuromorphic field. It concludes by offering an outlook for the potential next steps of the field.

In response to the well-known issues facing standard computing architecture, the neuromorphic computing field proposes new computing technologies and methods which harness the power of brain-like architectures and functions for a potential new era of efficient and versatile computing. With numerous technologies vying to be the backbone of this field in the coming years, it finds itself at a vital crossroads. At this critical juncture, we offer an overview of the history of neuromorphic computing, what the current status of the field is, and where it might go next. A brief review of the field's history is offered first, beginning with its roots in the coming twilight of standard architectures, and is followed by a review of the current technologies in the field and finally an outlook on the potential next steps in the coming months and years.

The neuromorphic field arose as a response to the challenges facing standard computers following the so-called "von-Neumann" architecture, developed during the Second World War and consisting of a memory storage component, a central processing unit (CPU), and a digital bus connecting the two, as well as input and output components [4]. As modern computing tasks continue to demand larger and larger amounts of data to be processed at increasingly faster speeds, two key limitations have become apparent in that standard format – the bottleneck effect of the digital bus, and the physical limitations of transistor-based technology (transistors can only be made so small before random statistical fluctuations on the atom level spuriously affect their behavior) [1]. Neuromorphic systems address these challenges by adhering closely to brain-like structures and functions, though the precise form of that technology is currently the subject of extensive discussion and active development.

With a few exceptions, most neuromorphic hardware operates in a so-called spiking paradigm, in which units (analogous to single neurons in the human brain) are only active when they receive or emit information, making these systems purely event-driven and considerably more efficient than standard systems. In addition to being event-driven, neuromorphic hardware also uses analog computation, representing data in physical quantities versus the binary digits (0s and 1s) used by digital hardware, which makes it both more efficient and more accurate. These systems still use digital signals, however, and the combination allows these systems to enjoy a form of "best of both worlds" between the two signal types, being able to take advantage of the accuracy of representation of continuous physical quantities provided by analog signals but also the efficient performance of logical operations offered by digital signals [2]. Multiple technologies operating under these principles are currently in development, with the major contenders being neuromorphic chips and photonic systems, the latter especially in the form of laser systems.

Neuromorphic chips deploy a physical network of artificial neurons and synapses connected in a brain-like manner. Such chips are highly energy efficient and well-suited for real-time and low-power applications. One example from the latest generation of such chips, Intel's Loihi 2, already includes up to one million physical "neurons" and has improved its processing capability tenfold over its predecessor, while also demonstrating a substantially increased capacity for use in multi-chip systems [5]. Chips are presently the frontrunner as concerns neuromorphic hardware using fully physical systems, while the second major subfield of development – photonic (or optic) systems – takes a different approach harnessing the unique properties of light.

Photonic systems still use physical units to represent neurons, but use light to connect them, allowing them to operate at speeds up to 10 GHz or more over long distances, potentially reaching levels of performance that outstrip even other photonic systems [3, 9]. Laser systems are the most common form of neuromorphic photonic hardware and are implemented by setting up one or more laser diodes to react to changes in incoming light that are analogous to the electric spiking activity of real neuron connections. Photonic systems can also be implemented with other bases, however, such as silicon structures or metamaterials (man-made materials with artificially engineered properties) [e.g. 8]. Lasers are naturally well-suited for spike-style computing due to their capacity for nonlinear behavior, and the capability to build photonic systems with existing technology, such as technology already utilized in the telecommunications field, is a key advantage of such systems, as it limits the development overhead needed to move these systems off the drawing board and into practical implementation [7].

While it is unclear what technology will form the backbone of the neuromorphic field in the future, it is clear that the innovations of this field and others like it will be vital to usher in a much-needed new era of computing that can meet the ever-growing needs of modern society. Looking forward, a fundamental next step will be proving neuromorphic technologies in key tasks. While some of these systems have been proven in fields such as image classification [e.g. 6], many remain largely untested in practical applications. Truly establishing neuromorphic hardware as the computing technology of the future will require thoroughly demonstrating that these systems can not only match the performance of current computing frameworks, but also address their shortcomings and surpass their abilities. A group effort across the field will be vital in this respect to demonstrate that these technologies are viable in application as well as theory. Collaboration will also be key in exploring the combination of various technologies, a currently overlooked avenue. Instead of the development of each proposed neuromorphic technology proceeding in its own semi-isolated "silo," exploration of mixed technologies that could harness the advantages of multiple subfields is additionally recommended (ex. neuromorphic chips which employ photonic connections between neurons).

Whether based in photonics, hardware circuits, combinations of those technologies, or another platform entirely, neuromorphic systems offer a brain-based solution to the modern computing crisis. At this critical stage of the field's development, the presently proposed presentation offers a summary of where we are now, what got us here, and where we might go next, which can provide a basis for centering those working across the field in the context of that field, providing a theoretical and contextual unity critical to further collaboration and innovation.

References

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