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Neuromorphic Electronics at BioCAS: A 20-year Legacy of Sparking Technology Revolutions

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***Abstract*—Motivated by the parsimony and robustness of the biological brain at computing, engineers have, over the last four decades, been emulating neurophysiology in silicon, i.e., neuromorphic engineering. The field has made significant contributions to our understanding of biological learning with accompanying implications in efficient sensing and artificial intelligence. Over the last two decades, BioCAS has been a conduit for disseminating research in neuromorphic engineering and other related fields. In such a milestone anniversary, we deem it appropriate to present a retrospective on the progress of the field with emphasis on the various contributions in neuromorphic electronics at BioCAS/CAS. At the risk of being inexhaustive, we offer some historical perspectives and key contexts that have shaped the community and the field as a whole. With the blessing of hindsight, we proceed to make bold projections on the future of the field.**

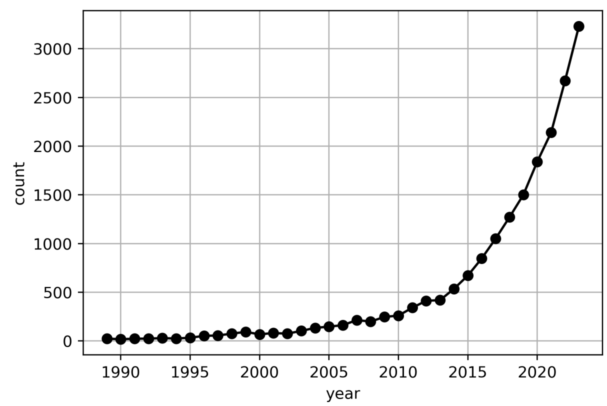

Fig. 1. Biblometric growth of neuromorphic publications. Generated by google scholar search with keywords *"Circuits and Systems" neuromorphic* from 1989–2023

I. Introduction

Neuromorphic engineering, as envisaged by Carver Mead, Paul Mueller, Eric Vittoz and Andreas Andreou, to name a few pioneers, has come far. What started as a sheer emulation and analysis-by-synthesis of natural intelligence and neurophysiology into transistor analog facsimiles has now pervaded the digital domains with immense implications and applications in artificial intelligence of today. From the earliest demonstration of retinomorphic vision by Mahowald, Boahen and Mead [1]–[3] and audition by Lyon and Mead [4]; interests and contributions to the field have and continue to grow significantly. The Circuits and Systems Society's (CASS) machinery, be it conference proceedings or journal transactions, has been pivotal in exposing the IEEE community to this growth. Unlike other dissemination venues, which focus more on completed work, the CASS allows developing ideas to be presented and vetted by its marketplace of ideas. Consequently, many far reaching technologies were first published within its pages, and are now ubiquitous in the scholarly lore and commercial domains.

The genesis of neuromorphic electronics at BioCAS (i.e. Biomedical Circuits and Systems) can be traced back to the CASS itself. A topic area and working group that centered on bio-inspired systems and circuits grew to a notable point, it gave impetus for a full-fledged technical committee and conference in the mid 2000s, with a focus on biomedical and biomimetic systems. Tor Sverre Lande, Yong Lian and Chris Toumazou led this initiative [5] as the first guest editors for a special session on Biomedical Circuits and Systems in the IEEE Transactions on Circuits and Systems (TCAS) 2005. On another front, independent annual workshops such as the Telluride Neuromorphic Cognition Workshop and the Capo Caccia Workshop Torwards Neuromorphic Intelligence have provided avenues for neuromorphs to meet and collaborate on pioneering projects, many of which found their ways into CAS proceedings and transactions. Over the last 30 years, both workshops have assembled the brightest minds in electrical and computer engineering, neuroscience, physics, and related fields to tackle fundamental questions on how our brains processing information and how that can be emulated physically and algorithmically and in silicon to solve important problems in information processing and understanding. Perhaps the most successful products of this endeavor are in vision, where monolithic image sensors (i.e. CMOS cameras), motion tracking chips (i.e. optical mouse sensors) and event-based cameras (dynamic vision sensors), to name a few, have become part of the commercial landscape. Start-up companies, as such Synaptics, Prophesee, INIvision and others, have produced vision sensors that can be found in mobile devices [6] and automobiles [7], [8] of today. These companies have partnered, or have been acquired, by larger players in the field, such as Sony, Samsung and Intel. In addition, neuromorphic computing, at the algorithmic and hardware fronts, is driving the third generation of neural networks – spiking neural networks (SNNs). It is worth mentioning that an expanse of papers on in-hardware learning and inference based on the bio-inspired principles have been presented at CAS/BioCAS

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and the biblometrics continues to grow as shown in Fig. 1. With the renewed interest in AI hardware, there exists a wealth of literature on neuromorphic design principles that will inform the design of sustainable hardware solutions to meet the ever-growing energy demands of modern AI. In this paper, we look back in time on some notable literature on neuromorphic electronics with emphasis on work presented at CAS/BioCAS. This endeavor is by no means exhaustive. Beyond this retrospective, we proceed to make informed speculations on the future impact of the neuromorphics on the artificial intelligence and medicine. We discuss several opportunities where CAS/BioCAS can continue to lead this frontier.

II. Impact Statement On Artificial Intelligence

The recent widespread successes of AI especially in the domains of large language modelling, computer vision and reasoning are accompanied by elevated training and inference costs by standard graphics processing units (GPU) hardware. It costs several megawatts of power and several millions of dollars to train state-of-the-art Generative Pre-trained transformer (GPT) network whose parameter counts ($\sim 10^{12}$) [9] are still well below the 10^{14} synaptic population of the human brain [10]. The brain runs on a mere 20 watts! This in itself foreshadows the inefficiencies of modern AI hardware. Our brains process information in a distributed and asynchronous manner. GPUs, while circumventing the von-Neumann bottleneck to an extent, do so in a sub-optimal clocked manner at gigahertz operating frequency scales compared to the milliseconds timescales of its biological counterpart. This paradox of speeds is yet another indication that our brains have evolved to do more with less. Asynchronous compute-in-memory (CiM) hardware such as IBM's NorthPole [11] have recently demonstrated an opportunity to transcend the GPU capabilities using biologically plausible computing ideas on state-of-the-art neural network models and datasets. On the argument of biological plausibility, the vaunted backpropagation algorithm isn't immediately obvious in our brains at least in its vanilla form [12]. On both hardware and algorithmic fronts, neuromorphs are developing more biorealistic learning techniques that take advantage of local synaptic plasticity rules for leveraging the spatiotemporal sparsities in activity present in neuronal networks. Mechanisms like spike-timing-dependent plasticity (STDP) are being extended to include a host of third factors that modulate pre- and post- synaptic activities, thus bridging the gap between traditional gradient descent-based models and SNNs [13], [14]. As low hanging fruits, there are also ongoing efforts to marry backprop with SNNs as an alternative to traditional recurrent neural networks (RNNs) as SNNs inherently leverage time and are conducive for interfacing with event-based data. Prominent among these efforts is the surrogate gradient approach [14]. This approach circumvents the dead neuron problem, i.e. non-differentiability of spiking activity, by using softer membrane voltage thresholding. There are promising efforts at software-hardware codesign with this approach. An interesting one is that by Cramer et al. [15] which combines pytorch (software) integration with the BrainScaleS-2, an analog neuromorphic hardware, on image and audio classification tasks.

On to the latest and greatest, large language models (LLMs) have been phenomenal on a host of generative and reasoning tasks. At the heart of LLMs are the multi-head attention units in their transformer networks. These attention units allow the network to form meaningful associations within the sequence of word embeddings at the encoder and decoder ends. The concept of attention in transformer networks isn't entirely novel especially in vision. Models of primate visual and audio saliencies [16]–[20] have long been formulated and translated into hardware [21] by neuromorphs and offer explainable alternatives to the "black-box" LLMs. While there is still ongoing debate on what attention in the brain really means, the baseline consensus borders on some kind of information filtering crucial to dedicating the limited biological resources on processing. While LLMs aren't as parsimonious as the brain, they can extract salient context in sequential data (be it audio, words in sentences, video or tokenized image stream). The emphasis is on 'sequence'. Somehow neural processing heavily depends on time. Even static sensory data are transduced into a temporal equivalent, i.e. spike encoding. Our eyes during static scene viewing, constantly move in a saccadic manner to generate some kind of temporal contrast. And for data that are inherently temporal, e.g. audio and motion, mechanisms like rate adaptation and refractoriness allow for judicious processing. Why bother on a signal that isn't changing much? In other words, the nervous system inherently handles entropy really well [16].

Finally, neuromorphic sensory electronics are today being integrated with SNN learning circuitry to minimize the energy and latency [22]. Such efforts will inform the next generation of greener and reliable intelligent systems.

III. A Survey Of Contributions

By far, our brains offer a template to engineer efficient artificial intelligence (AI). This piece of tissue working in tandem with the peripheral nervous systems coordinates a slew of sensory information that arrive from our five senses in a fault-tolerant manner. By adopting inherently sparse computation, biological learning has evolved to focus on salient elements in sensory data. This is evident by contrast and orientation selectivity present in the retino-cortical processing of visual input; the spatio-spectral mapping of auditory input along the cochlea, to center-surround mechanism that aid in tactile perception. Over the years, a number of contributions have been made at CAS/BioCAS at building circuits and systems that take advantage of such biological efficiencies. Here, we review a number of significant papers at CAS/BioCAS transactions and conference proceedings largely focusing on subthreshold design, neuromorphic sensing, control, learning and machine learning (ML) accelerators and applications in robotics, prosthetics and neural implants and interfaces. While we do our best to categorize the various contributions, there exists significant overlap, by reason of shared applicability, in the various categories of circuits and systems, and thus we ask the reader to pardon any potential repetitiveness.

A. Subthreshold Circuits

One of the most important observations made by early neuromorphs was to see the similarities that existed between neural biophysics and transistor physics particularly in the subthreshold regime. Classical neural models, from Lapicque to Hodgkin-Huxley, possess exponential dynamics (by means diffusion of charge carriers) very similar to the current-voltage (IV) dependence of the MOS transistor in subthreshold [1]. The advantages of this MOS regime include the low-power operation – a minute gate voltage well below the device threshold voltage, is capable of eliciting a small yet useful amount of current (typically in the nano amperes regime or lower), and cheaper arithmetic costs especially in current-mode – by taking exploiting Kirchhoff laws and the translinear (log-antilog) principles, operations like addition and multiplication were significantly cheaper than their digital equivalents. One of the earliest efforts at popularizing the design style with an emphasis on silicon neural systems was presented at ISCAS by Andreou in 1990 [23] and elsewhere [24], [25], the fundamentals of the MOS subthreshold operation and the translinear principle were presented along with a host of applications in neural system circuits – winner-take-all (WTA) circuit for realizing inhibitory competition, and a current conveyor circuit for implementing bidirectional electrical synapses (i.e. gap junctions). Both circuits were then captured in an extensive circuit (i.e. a cascade of silicon retina units) of the outer-plexiform layer of the retina with an accompanying demonstration of the Laplacian (Mexican-hat) center-surround spatial filter. Several subthreshold circuit systems have since followed at ISCAS and BioCAS with notable ones being [26], [27] to mention a few.

B. Neuromorphic Vision

The earliest demonstration of neuromorphism was in retinomorphic vision – Misha Mahowald's retina pixel circuit [1], [28] subsequently improved by Boahen [2] captured the various intricacies of the primate retina – contrast detection, local automatic gain control, spatiotemporal bandpass filtering and adaptive sampling. Various improvements and derivatives have since followed [29], [30] to what is now referred to as event-based cameras. The fundamental principle behind these sensors is to capture temporal contrast in a visual scene instead of the absolute pixel intensities, as done in classical CMOS active pixel imagers (APS). Through logarithmic compression of intensity changes, retinomorphic imagers possess high dynamic range (HDR) at sub-microsecond time resolutions useful for high-speed imaging. Here we discuss some key contributions to neuromorphic vision, visual motion estimation and tracking, among other related applications that have appeared in the CAS/BioCAS venues.

We begin with Delbruck and Mead's adaptive photoreceptor circuit [31]. This well-adopted and compact circuit was composed of a source-follower receptor (i.e. a photodiode placed at the source of a feedback MOS transistor) combined with an amplification stage with feedback via a capacitive divider branch and a novel adaptive element. The feedback transistor contends with the transduced photovoltage and effectively clamps the voltage. The purpose of this circuit was to impute the simultaneous ability of the retina to adapt to slow and rapid changes in illumination. The magic of this circuit occurs in the adaptive element, which at a simplified level is a parallel combination of two diodes of opposite polarities (in detail composed of an MOS-bipolar transistor combination). This creates a variable resistance that is high for small signal changes and low for rapid large signal swings. The adaptive element interacts with a storage capacitor to impute a corresponding variable time constant set by the rate of change in the incident photocurrent. This work subsequently evolved into the well-known dynamic vision sensors (DVS) [32]. Another biomorphic silicon retina implementation was that by [33]–[35]. This implementation mimicked the phototransduction in the octopus retina, i.e. direct conversion of light intensity into spike output unlike other retinal pathways that first represent luminous intensity as analog signals e.g. cones and rods in primate retinae output analog potentials that traverse the outer and inner plexiform layers to the ganglion cell layer where spikes are emitted. This implementation also included an event-based communication protocol, i.e. address event representation (AER), for arbitrating and routing the various spike outputs in an array of the silicon retina pixels. For an extensive coverage of event-based vision sensors, the reader may refer to an earlier ISCAS comprehensive survey on this subject matter [29]. Other exotic designs include a hybrid active pixel sensor (APS)-DVS imager by [36] (TBioCAS 2017) for color imaging and an application in neural (GCaMP6f - calcium) imaging. Speaking of color, the reader may also find an earlier infrared imager work by Pouliquen et al. [37] presented at ISCAS 2000. Finally, a number of competing pixel designs can be found in [30], some of which have been presented or demoed at ISCAS/BioCAS – [38]–[40] while others have been commercialized.

From phototransduction, we move to preprocessing; significant preprocessing occur at various layers of the retina. The outer plexiform layer through horizontal cells performs spatiotemporal filtering. This filtering behavior has been emulated in silicon by Serrano-Gotarredona et al. [41]. This work demonstrated, by simulation, an event-based filtering for any convolutional kernel that can be decomposed into (x, y) components similar to 2D-to-1D modification of the Adelson and Bergen's model by [42]. Serrano-Gotarredona et al. [41] adopted various current-mode principles for spatial filtering. An extension of this work with chip results can be found in TCAS 2006 [43]. A related work is that by Lopich and Dudek [44] – an asynchronous Single Instruction/ Multiple Data (SIMD) cellular processor.

Next, we explore the space of visual motion estimation and tracking. Early works in this direction were mostly focused on emulating the fly visual system for reasons of its biological simplicity as compared to others like that of primates, i.e. an ommatidia count of only $\sim$4000, a relatively lower resolution sensory machinery. With such limited pixel density, the fly is able to navigate obstacles very quickly. Emulation of this phenomenon holds clear implications for robotic, drone and automobile navigation. The classic Hassentein-Reichardt model [45]–[47] captured these intricacies in a spatiotemporal correlation model for elementary motion detection at its introduction well before the 1980's. This model has since formed the basis for most motion detection implementations in VLSI. We discuss a few of such emulations. One of the earliest atttempts at ISCAS is by [48]. This current mode subthreshold MOS circuit realized retinal functions like spatial filtering using center-surround mechanism, delay and gain control via a translinear multiplier. Authors demonstrated a positive correlation between velocity input (as a current) and an output current. Other early works include that by [42], which presented a VLSI implementation of a modified version of the Adelson and Bergen's model with two 1D (instead of the typical 2D) motion detectors. The same authors preceded this with a silicon implementation of a Reichardt-like motion detector [49] and succeeded it with the dual imaging and centroid motion localization chip [50]. Indiveri [51] in TCAS '99 also presented an analog VLSI (aVLSI) sensor for visual tracking. At the base of the sensor is the earlier-mentioned adaptive photoreceptor [31], interfaced with spatial derivative, edge polarity detection, WTA and position-to-voltage stages (in a bottom-up order). The work proceeded to integrate the sensor on a robot and clearly was one of the earliest attempts at embodied neuromorphic intelligence. Etienne-Cummings et al. [52] also demonstrated a foveated silicon retina for visual tracking. This vision chip was composed of two sensor clusters – a dense packing of 9$\times$9 centroid pixels for smooth-pursuit tracking and 19$\times$17 peripheral (larger) pixels for saccadic target acquisition. Shih-Chi Liu [53] also demonstrated an aVLSI implementation of fly motion computation using adapted version of [31] as photodetector. A noteworthy VLSI implementation of motion processing presented elsewhere is that by Sarpeshkar et al. [54]. Another effort also presented elsewhere in 1996 that saw commercial success was the optical motion-tracking chip designed by Arreguit, van Schaik and co. [55]. This neuromorphic design made it in the Logitech TrackMan Marble mouse [56] which is still on the market after nearly 3 decades [57]. Recent vision work at BioCAS include work by [58] involving a convolutional neural network integration with the ATIS event-based camera for low latency object recognition in an FPGA. In a similar light, [59] at BioCAS 2014 presented an FPGA implementation of event-based processing for CNNs (composed of a cascade of 2D Gabor kernels) on event streams from a DVS chip. [60] demonstrated 2D visual motion sensor (with an effective sampling rate of 1 kHz) synthesized from a 20$\times$20 silicon retina and a 16-bit DSP PIC microcontroller.

C. Neuromorphic Audition

While neuromorphic sensing has been dominated over the years by vision, the auditory domain has also been explored extensively. Since pioneering work by [4] that modeled cochlear fluid-dynamic wave propagation as a cascade of filter responses, a wide variety of work has followed. [61], [62] in TCAS '97 & '98 presented sensory preprocessing silicon implementations to extract salient audio features via zero-crossing detection and computation of multispectral band energies. Beyond transduction, Cauwenberghs and others have innovated several VLSI systems for auditory computation. These include subthreshold circuits for audio processing [63], [64], low-power gradient flow acoustic localization [65], a theoretical demonstration of an independent component analysis-based blind source separation approach of monoaural acoustic signals which leads to electronic implementations [66]. van Schaik [67] presented an aVLSI model of an inner hair cell, i.e., a sensory neuron of the cochlea that feeds ganglion cells to transduce travelling sound waves into spikes. The logistic relationship between the input displacement (captured as a voltage in the model) and the output response (as a current) was reproduced. van Schaik and Liu [68] presented AER EAR at ISCAS 2005. This project spawned several publications at CAS – [69]–[71] The AER EAR was composed of a pair of matched silicon cochleae whose readout interface was facilitated by the AER protocol. The protocol is a standard communication protocol used by most event-based sensory/ processing array to circumvent the cost of explicit dense point-to-point wiring. This is achieved by arbitrating and multiplexing communication of events in time. The principle was developed at the beginning of the field of neuromorphic engineering and is still useful to date [72]–[76]. Other early work in audition includes the design of a cochlea implant by Lande et al. [77]. Recent auditory work at BioCAS includes that by [78] – an FPGA implementation of a Cascade of Asymmetric Responses (CAR) model and [79] fusion of event-based visual and audio sensory data (from DVS and FPGA-based electronic cochlea) for localization and collision avoidance.

D. Other Sensory Modalities

Though comparatively fewer efforts have been made outside of vision and audio, there are several promising works to emulate tactile and olfactory perceptions in silicon. Such works are very recent and include that by Bartolozzi & co. [80], [81] and Thakur & co. [82], [83] and have in recent times heralded an interest in touch and even pain. Bartolozzi's tactile sensor [81], [84] leverages the change detection of the DVS for the pressure transducing piezoelectric-oxide-semiconductor field effect transistor (POSFET), instead of the photodiode/ phototransistor used in most retinomorphic vision sensors. This system was also equipped with an AER readout to facilitate an asynchronous tactile event recording at the array level. This DVS-like integration points to the versatility of neuromorphic sensory systems. The potential to repurpose these electronics in other domains is telling and yet to be fully tapped. Event-based tactile sensing has been integrated with the iCub humanoid robot [85], [86] . A roadmap to include other event-based perception towards engineering modernday embodied neuromorphic intelligence has been provided by [87]. Thakur's group took a different approach that was geared much more towards clinical neurorehabilitation; they designed *e-dermis* [83], a tactile sensing sheet of piezoresistive material patterned with conductive trace material and covered on both sides with a rubber material. Transduction into the spike domain involved feeding the pressure output of the *e-dermis* into an Izhikevich neuron [88]. Through transcutaneous electrical nerve stimulation in an amputee, they could extract stimulus parameters that elicited innocuous and noxious tactile perceptions.

Although research into olfactory electronics is still nascent, we can envisage that the neuromorphic sensing mechanism will not be too different. As long as some form of change detection can be captured in chemosensors, the problem might be half-solved. VLSI attempts at this include that by Koickal et al. [89] and Beyeler et al. [90]. Chakrabartty et al. [91] have provided some fundamental ideas on how to realize bioinspired olfaction with an emphasis on discriminating high-dimensional odor mixtures and background odor suppression.

E. E. Neuro-dendro-synaptic Circuits and Arrays

At the foundation of cortical processing are the diverse neural dynamics. Single-neuron electrophysiology has been modeled to varying degrees of biological plausibility and computational efficiency [92]. Considering decades-old interests in the implementation of artificial neural networks (ANNs), it comes as no surprise that silicon neurons have seen numerous VLSI implementations. At the outset of the field, Mead in his Analog VLSI and Neural Systems book [1] introduced the axon hillock neuron. This simple integrate-and-fire (IF) neuron circuit took advantage of positive capacitive feedback to elicit a spike once the 'membrane potential' cross a threshold. Mahowald and Douglas [93] followed this up with a more biorealistic silicon neuron that integrated sodium and potassium current in its dynamics. Three decades on, an expanse of silicon neuron designs has followed, a number of which have appeared at CAS/BioCAS. As in previous sections, we outline a selection of such sequels. An impressive review of single silicon neuron implementations can be found in [94]. Thus, we waste no time on this, other than mentioning those that have appeared at BioCAS – *NeuroDyn* (Hodgkin-Huxley neuron with synaptic dynamics) [95]–[98], Mihalas-Niebur (MN) (generalized linear IF) neuron [99], a conductive-based neuron [100], bifurcative approach to silicon neuron design [101] (which ultimately informed *Neurogrid* [102], an array implementation), digital (FPGA) [103] and analog [104] implementation of the Izhikevich Neuron, the Fitzhugh-Nagumo neuron [105], digital (FPGA) realization of the Wilson neuron [106] among others. We also list a number of synaptic, dendritic, and array implementations. At the array level, Yu et al. [107] at BioCAS 2012 as part of the HiAER-IFAT project presented an array of 65k IF neurons with accommodation for synaptic routing via AER. They followed this up with [108]. Molin et al. [18] presented an array of MN neurons synthesized from leaky integrate-and-fire (LIF) neurons. Cassidy et al. at BioCAS 2007 [109] and 2008 [76] presented an array of LIF neurons in an FPGA and an approach to interconnecting these neurons via a wireless AER respectively. Wang and Liu [110] presented a programmable dendritic and neuron array on a single chip. The dendritic units possessed excitatory (AMPA, NMDA) and inhibitory (GABA) receptors. On the scalability front, Morella et al. [111] demonstrated a modular asynchronous routing scheme for neuron arrays. Other array implementation works that have appeared in BioCAS include an optical flow estimation method using the IBM TrueNorth chip (an asynchronous neurosynaptic chip with a million neurons, a precursor to the more recent NorthPole chip) and DVS sensor [112] and Frenkel's ODIN [113] and MorphIC [114] chips (both of which are digital multicore SNN implementations with learning capabilities).

F. Neuromorphic Learning

There have been attempts at translating bioinspired learning algorithms in silicon; which is an obvious progression if one manages to engineer such expressive computational engine as neurosynaptic arrays. Though the structure of modern AI models such as ANNs appears to be biologically motivated, the training and inference techniques used are quite disparate from their biological counterparts, not to mention the inefficiencies of the hardware on which they run. Learning is the pinnacle of any intelligent system; neuromorphic systems have been built over the years to do so at brain-level efficiency. Several of such learning electronics have been presented at CAS/BioCAS. We outline some of them here. Early works include that by Andreou and Cohen [115], [116] – a current mode implementation of the Herault-Jutten autoadaptive network (ISCAS '93), Cauwenberghs' A/D converter chip with reinforcement learning (ISCAS '97), Cohen et al. [117] mixed-mode VLSI realization of adaptive resonance theory algorithm. Presented elsewhere but worth mentioning here is Cauwenberghs' Kerneltron [118] – VLSI implementation of the support vector machine algorithm with a sequel by [119]. Besides these, most learning efforts have been biased towards Hebbian learning. morphIC [114] and ODIN [113] made accommodation for learning via STDP. Similar in-circuit/on-chip learning has been demonstrated by [120]–[123]. An interesting demonstration of generative learning relevant to current wave of AI research, is that by Pedroni et al. [124] (BioCAS 2016). There, authors through a Restricted Boltzmann Machine (RBM) approach running on the TrueNorth hardware demonstrated the generative pattern completion task. Other learning work includes that by Donati et al. [125] involving the use of the DYNAP-SE neuromorphic chip for training a surface EMG signal classifier.

G. Neuromorphic ML Accelerators

Today's ML models require a large number of multiply-and-accumulate operations that CPUs cannot readily provide. This has led to an overreliance on GPUs. While GPUs have opened the frontier for faster training on larger batch size of data, their energy efficiencies are poor. Training costs of LLMs at scale easily run into megawatts and millions of dollars [8]. In what is a tale of prescience, neuromorphs have been in the business of engineering accelerator hardware for a while now. An early work is the charge-based vector-matrix multiplier chip by Genov and Cauwenberghs [126]. Recent work includes an embebbed CiM hardware for learning and inference at the edge by Mendat et al. [127] (ISCAS 2023), which reported phenomenal energy metrics such as 1-bit MACs at 45fJ/Op and 8-bit operations at 1.47pJ/Op and a mere 30mW power consumption on a character recognition task. At ISCAS 2016, Sanni et al. [128] also presented a charge-based vector-vector multiplier chip in 65nm that recorded 68.27pJ/Op. Chakrabartty and Cauwenberghs [129] recently presented arguments on the performance walls in ML and neuromorphic systems. They point out the promising potential of resonant adiabatic CiM hardware, which surprisingly supersedes the human brain in energy efficiency (i.e. 1 aJ/MAC in FDSOI vs 1fJ/SynOp in the brain). Another exciting frontier is that of memristive and spintronic CiM – Wan et al. [130] and Sengupta et al. [131]. Other efforts include the DeltaRNN accelerator by Gao et al. [132], RAMAN accelerator by [133], [134] and Frenkel's convolutional accelerator [135].

H. Neuromorphic Control, Prosthetics, Robotics and Implantable Electronics

Significant contributions have also been made in the realms of control, robotics, and neurorehabilitation. One prominent subject here is locomotion – by modelling the central pattern generators in the vertebrate spinal cord, Etienne-Cummings and co. in a series of BioCAS papers [136]–[138] demonstrated the restoration of lost gait function. Other limb prostheses research are that by Tang et al. [139] involving the use of the DVS in aiding grasp in upper limb prostheses. On another front, Turicchia and Sarpeshkar [140] have demonstrated aVLSI circuits of the vocal tract specifically modelling the constriction in the glottis and supraglottis. Cochlear implant work has also burgeoned with efforts by Germanovix and Toumazou [141] – a current-mode analog cochlear implant, Lande et al. [77], among others. Hageman et al. [142] have also demonstrated a VLSI realization of a multichannel vestibular implant with *in-vivo* testing for restoring vision- and posture-stabilizing reflexes. Etienne-Cummings, Tapson and co. [143], in an interesting demo of the color glove at BioCAS 2008, showed how the visually impaired could perceive color via haptic feedback. Meanwhile, developments in brain-machine interfaces continues unabated – Corradi and Indiveri's [144] event-based neural recording platform with learning capabilities that demonstrated massive data compression at the sensor front by passing only rapid signal changes.

IV. Outlook

The CAS/BioCAS community continues to be major players in the early development of technologies that are central to the search for artificial intelligences that can match their natural counterparts. We have so far focused mainly on the synthesis of biology in silicon integrated circuits, but this is now changing. Instead, we are now witnessing much more scrutiny of the material science of the components used to realize neuromorphic computation because we are now able to implement nanoscale computing elements that are even more similar to their biological counterparts than transistors. The nanoscale devices are grouped in the general term of "memristive devices." Memristors will continue to push the development of new architectures for large scale neural systems, machine learning and AI accelerators. Beyond emulation of biological systems with inorganic materials, we are also entering an era where the line between organic and inorganic intelligences are beginning to fade [145]–[149]. Our ability to culture organoids with all the computational machinery of the nervous system, to interface them to computational electronics and to use them to participate in real-time computation will open the door to mixes of *in-vivo* and *in-vitro* processors that will completely revolutionize artificial intelligences. We will be able to guide the development of the organoids using *in-silico* electronics and take advantage of the vast number of variables that exist in the organic matter, most of which cannot be emulated *in-silico*, mainly because we do not know how they operate. What we learn from these hybrids will also dictate how we design the next generation of brain-machine interfaces, and how we help the human condition through healthcare applications. Again, the CAS/BioCAS community has already been seeding this path and will be central to the technologies that are to come.

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