Neuromorphic Computing Based on Wavelength-Division Multiplexing

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(Invited Paper)

I. INTRODUCTION

Artificial neural networks (ANNs), inspired by the human biological brain, have achieved unprecedented success in a wide range of applications ranging from image recognition to sophisticated board games [1], [2], [3], [4], [5], [6], [7], [8], [9], [10], due to their capability for learning to be able to process unknown data intelligently. ANNs are mathematical network models formed by densely interconnected neurons, with the ability to address complicated tasks, limited only by the scale of the network (i.e., number of neurons and synapses). As such, the number of operations and parameters of ANNs, which determine the hardware’s computing power, scale exponentially with performance, including key attributes such as accuracy [11].

However, while more advanced applications of ANNs bring about ever-higher demands of the hardware’s capabilities, the performance density and energy efficiency of leading electronic hardware platforms face severe limitations, as reflected by Moore’s law [11], [12], [13], [14]. The performance density (i.e., number of operations performed within a given chip scale) can no longer increase beyond where Moore’s law ends, at device feature sizes of around 5 nm. As a result of reaching this limit, the energy efficiency of memories has shown little improvement since 2015. This is due to two fundamental limitations – the so-called electronic bandwidth bottleneck and the von-Neumann bottleneck [15], [16]: the former limits the clock rate of electronic devices to ~2 GHz, while the latter introduces high energy consumption during the process of reading and writing data back and forth.

Optical neural networks (ONNs), are promising next-generation neuromorphic accelerators for ANNs, since they can potentially offer ultra-large bandwidths of >30 THz in order to reach dramatically accelerated computing speeds, together with low power consumption due to operating inherently in the analog regime [17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63], [64]. To realize ONNs, weighted synapses forming the interconnections between neurons need to be implemented with multiple physical paths established within the temporal-, spatial- and wavelength-division parallelism [17], [18], [19], [20], [21], [22], [23], [24], [25]. For example, time-delayed optical loops are employed to achieve reservoir computing or spiking neural networks [26], [27], [28], [29], [30], [31], [32], [33], [34], [35] that can store over one thousand nodes within the cavity. Integrated photonic waveguides [36], [37], [38], [39] and free-space optics [40], [41], [42], [43], [44], [45] have been employed in order to achieve synaptic connections spatially. Further, multi-wavelength sources combined with weight bands [46], [47],
50 GHz limited by analog-to-digital converters of optics. While the loaded data generally occupies an electronic wavelength domain. Wavelength division multiplexing (WDM) can be used to achieve synaptic connections within the wavelength domain. The overall architecture of a typical WDM system.

Fig. 1. The overall architecture of a typical WDM system.

[48], [49], [50], [51], [52] or wavelength-sensitive elements [53], [54], [55] can be used to achieve synaptic connections within the wavelength domain. Wavelength division multiplexing (WDM) techniques are critical to fully exhaust the wideband advantages of optics. While the loaded data generally occupies an electronic bandwidth < 50 GHz limited by analog-to-digital converters and generic opto-electronic interfaces, the >30 THz optical bandwidth needs to be fully exploited by introducing multiple parallel wavelength channels to cover the full optical bandwidth.

Optical frequency combs (OFCs), offering a large number of equally spaced wavelength channels, are powerful tools for communications systems and neuromorphic computing in order to significantly enhance the capacity or parallelism of the system [65], [66], [67], [68], [69], [70], [71], [72], [73], [74], [75], [76], [77], [65], [66], [67], [68], [69], [70], [71], [72], [73], [72], [75], [76], [77] in contrast to discrete laser arrays. During the past two decades, the advance of photonics fabrication techniques has led to the production of integrated OFCs in different forms, offering remarkable advantages in terms of the system's size, weight, power consumption, and cost [77]. Existing integrated OFCs can be divided into several categories (Figs 2, 3) based on the underlying physical origins, including: a) Kerr frequency combs, or microcombs [78], [79], [80], [81], [82], [83], that originate from parametric oscillation in an integrated micro-ring resonator (MRR); b) mode-locked lasers that employ gain media, such as Erbium-doped fiber amplifiers, in order to sustain oscillations and mode-locking mechanisms, such as saturable absorbers to yield pulsed outputs [84]; and c) electro-optically generated microcombs that employ modulators to take advantage of their second-order nonlinearity to introduce sidebands centered around a certain optical carrier [85].

For neuromorphic optics, the three categories of OFCs each have their own unique advantages and disadvantages. EO combs are more flexible in terms of tuning the comb spacing, although with the additional costs of external RF sources and oscillators. Mode-locked lasers support turn-key operation, offering low-noise coherent comb lines; however, their bandwidths are limited by the gain bandwidth of optical amplifiers (e.g., Erbium-doped fiber amplifiers that operate in the C band from 1535-70 nm), limiting the computing parallelism. Microcombs, on the other hand, arguably offer the greatest advantages to enhance the performance of ONNs.

Microcombs are powerful integrated OFC sources, due to their compact footprint and ultra-wide bandwidths capable of octave-spanning operation, supported by broadband nonlinear parametric gain [78], [79], [80], [81], [82], [83]. Microcombs originate from parametric oscillation within high-Q micro-resonators, which can be realized either in integrated form, such as micro-ring resonators [83], or in 3-dimensional form, such as spheres or rods [78]. The key to microcomb generation is to obtain sufficiently high parametric gain, which is directly determined by the strength of the third-order nonlinearity of the material platform and the Q factor of the resonator (i.e., low linear and nonlinear losses) [79]. For high Q-factor micro-resonators, the optical intra-cavity field can be resonantly enhanced in order to initialize nonlinear phenomena that otherwise would generally...
require high optical power — such as modulation instability gain and parametric oscillation. In 2010, parametric oscillation based on integrated platforms was first reported [83], [86], [87], which revealed the ultimate potential of microcombs to be mass produced together with other optical components on a single chip, employing well-established CMOS platform fabrication techniques.

While microcomb generation often requires a high external pump power that brings about limitations in terms of energy efficiency and footprint (i.e., high-power amplifiers are unavoidably needed), significant effort has been made to reduce the parametric oscillation threshold. On the one hand, novel material platforms [88], [89], [90], [91], [92], [93], [94], [95], [96], [97], [98], [99], [100], such as SiC [97] and AlGaAs [95], [96] can exhibit significantly higher third-order optical nonlinearities, while on the other hand, advances in nanofabrication techniques, such as the Damascence reflow process and multi-mode waveguides [101], [101], [102], increase the Q factors to enhance the build-up optical fields in the micro-resonators. To date, a nonlinear coefficient of $n_2 = 2.6 \times 10^{-17} \text{ m}^2 \text{ W}^{-1}$ has been achieved with AlGaAs waveguides, resulting in an ultra-low threshold power of 0.036 mW [95]. Q factors of over 10 million have been achieved with the Damascence reflow process for integrated micro-resonators [101], and these advances indicate that microcombs can be directly generated using a generic pump laser source where high-power amplifiers are no longer needed, albeit specific pump detuning control mechanisms are still necessary.

Governed by the Lugiato-Lefever equation [79], multiple parameters contribute to the rich dynamics of microcombs (Fig. 4). These include the pump power and detuning (perturbed by thermal effects) that determine the intra-cavity pump power as well as the nonlinearity that governs the oscillation threshold and comb states. Also important is the dispersion that balances...
the nonlinearity, which together affect the comb bandwidth. Different nonlinear effects and their impact on microcomb generation have been investigated, including the third-order nonlinearity (degenerate and non-degenerate four-wave mixing, or FWM) that lead to primary combs, also termed Turing patterns (with comb spacings at multiple free spectral ranges (FSRs) of the micro-resonator). Using delicate pump detuning control, single solitons [89], multiple solitons [103], [104], and breathers [105], [106], [107], [108] can be generated. On the other hand, mode crossings can lead to soliton crystals [109], [110], [111], [112] which display a range of attractive features, such as ease of generation and more stable and efficient operation. Finally, using a combination of gain and loss, normal dispersion and mode crossings can lead to dark solitons that offer similar advantages to soliton crystals, such as higher energy output [113]. Combs based on Raman scattering, a molecular-scale process where a Stokes photon and an optical photon are generated from a pump photon, can enable broadband Raman gain and Stokes solitons coexisting with Kerr combs [114]. Brillouin scattering, a lattice-scale process where a backward scattering Stokes photon and an acoustic phonon are generated from a pump photon, introduces narrowband Brillouin gain at ∼10 GHz away from the pump. As such, Brillouin combs are observed in large resonators with FSRs matching the Brillouin gain bandwidth [115], [116].

In parallel with the development of microcomb material platforms, advanced pumping methods have been demonstrated aiming at, on the one hand, overcoming the thermal effects of the micro-resonator that severely perturb the wavelength detuning control for soliton generation, and on the other hand, further reducing the complexity and footprint of the overall comb setup. Typically, the pump laser can take a number of different forms, including continuous-wave (CW) lasers that operate at a single wavelength, [89], [103], [118], [119] dual CW lasers with one serving as an auxiliary laser [120], [121]; and with optical pulses that feature much higher peak power to initialize parametric oscillation [122], [123].

Soliton generation requires that the pump wavelength be swept from the blue to red shifted side of the microresonator’s resonance, finally landing in the soliton step region, during which the thermal effects of the micro-ring resonator shift the
Fig. 5. Pumping methods of microcombs. Figures are adapted from [103], [120], [124], [125], [126], [127].

resonance with respect to the intra-cavity power [89] (Fig. 5). Since the single soliton state features a much lower intra-cavity power compared to the originating chaotic state, deterministic soliton generation remains challenging and requires delicate external control of the pump-resonance detuning because of the inherent resonance shift that happens at the onset of soliton generation. Classic detuning control methods that have been widely employed and verified include fast wavelength/resonance tuning to reduce the accumulated heat during the detuning sweeping process [103], [119], as well as power kicking methods to manipulate the resonance shift induced by thermal effects and the optical pump power [108]. Recently, advances have been made following the development of hybrid integration techniques, allowing more sensitive control of the detuning in both forward and backward directions that enable more accurate control of the single and multiple soliton states [89]. Dual pump approaches that employ an auxiliary laser to balance the thermal effects induced by the pump laser [120], [121] have been successful. Heterogeneously integrated laser and micro-resonators will also eventually enable mass production of the microcomb system [124], while injection locking approaches that lock the detuning via cross- and self-phase modulation effects to achieve turnkey microcomb generation [125], [126] have been very successful. Finally, self-oscillating pump generation methods significantly reduce the pump power and enable high energy efficiency laser cavity soliton states [127].

All of these significant advances have collectively led to microcombs that exhibit an ever-increasing maturity for practical applications, providing a wideband, high-energy-efficiency, compact, turnkey and mass-producible comb source for WDM systems [128], [129], [130], [131], [132], [133], [134], [135], [136], [137], [138], [139], [140], [141], [142], [143], [144], [145], [146], [147], [148], [149], [150], [151], [152], [153], [154], [155], [156], [157].

III. OPTICAL NEURAL NETWORKS BASED ON WAVELENGTH-DIVISION MULTIPLEXING

While electronic neuromorphic hardware faces increasingly large gaps between the desired and achievable performance in terms of computing density and energy efficiency, bounded by
Moore’s law, optical neuromorphic accelerators have attracted significant interest over the past decade, mainly due to their ultrawide optical bandwidth and low power consumption enabled by their inherently analog architectures [17], [18], [19], [20], [21], [22], [23], [24], [25].

The key to accelerate computing for artificial intelligence applications is to achieve the basic mathematical operations optically in a highly controlled manner, such that the overall parallelism and data throughput can be significantly enhanced for high computing power and large-scale fan-in/-out. High data throughput can be achieved with high-speed electro-optical interfaces, including electro-optical modulators and photodetectors that can reach over 50 GHz in bandwidth. High parallelism, needed to process large-scale data such as images or speech, can be implemented with multiplexing techniques that have been widely used in optical communications [17], [18]. The parallelism of optical neural networks mainly determines the fan-in/out of the network, which governs the networks’ capability of processing large-scale data. Likewise, the number of connections between the neurons denotes the networks’ capability in terms of processing complicated tasks. Typical techniques to enhance the parallelism employ space-, time-, or wavelength-division multiplexing (Fig. 6). ONNs based on space-division multiplexing (SDM) have been achieved with integrated photonic circuits [36], [37], [38], [39], diffractive lens and others [40], [41], [42], [43], [44], [45], where parallel input nodes are realized spatially in the form of different optical waveguide ports or pixels of the lens. Matrix multiplication operations have been achieved using intensity modulation/loss management of the optical field and mutual interference paths. ONNs based on time-division multiplexing (TDM) convert the input data and/or synaptic weights into temporal waveforms for matrix/vector operations [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], which requires additional optical buffers...
to achieve the accumulation process. The advantage of TDM techniques is that they are potentially capable of updating the synaptic weight at high speed in order to significantly accelerate the training process for the neural networks. However, they generally require other multiplexing techniques to enhance the computing power, due to their inherent sequential/serial operational methods.

Wavelength-division multiplexing (WDM) is a unique technique enabled by optics, which offers many advantages over purely electronic methods. Supported by the ultra-wide optical bandwidths up to 10s of THz, 100’s of wavelength channels can be established for parallel data processing of neural networks, thus leading to significantly enhanced computing speed – similar to the significantly enhanced data transmission capacity for WDM-based communications systems. Current WDM-based ONNs [46], [47], [48], [49], [50], [51], [52], [53], [54], [55] can be generally categorized into two types, according to whether the wavelength channels carry identical or different data. Individually modulated wavelength channels [46], [52] enable potentially higher flexibility and parallelism, capable of performing generic matrix multiplication operations. However, they also require large arrays of modulators with well-matched wavelength multiplexers/demultiplexers, which remains challenging to be integrated and synchronized on chip without significant increase in complexity and cost. For example, for a 50 GHz-spacing microcomb source, over 80 wavelength channels can be established in the C band, which in turn requires over 80 modulators. In parallel, simultaneously modulated wavelength channels [54], [55] are potentially much more straightforward to implement and integrate, as only one modulator is needed to broadcast the input data. The drawback to this approach is that, despite the increase in parallelism, the overall computing power is limited for generic matrix operations. This is true for all broadcast-and-weight systems used for matrix multiplication [55], where the input data is implemented as serial temporal waveforms. Here, WDM does not in fact lead to an enhancement in the computing parallelism and so the computing speed is similar to the data rate [54].

IV. WDM-BASED CONVOLUTION ACCELERATORS

Recently, [54] convolution accelerators have been proposed based on a time wavelength interleaving approach, which avoids the trade-offs mentioned above and has achieved high computing power within a compact footprint. The operation principle of the convolution accelerator is illustrated in Fig. 7. For vector convolutions between a $1 \times L$ data vector and a $1 \times R$ weight vector, the data vector is converted to a temporal waveform $X[n]$ via digital-to-analog converters, where $n$ denotes discrete temporal locations of the symbols. The weight vector is then mapped onto the power of optical comb lines as $W[1 \leq i \leq L]$ ($1 \leq i \leq R$, $i$ increases with wavelength). Via electro-optical modulation, $X[n]$ can be broadcast onto all of the comb lines simultaneously, yielding weighted replicas as $W[1 \leq i \leq L] \cdot X[n]$. Next, the weighted replicas are progressively delayed via dispersion, with the delay step between adjacent wavelength channels equaling to the symbol duration of $X[n]$, thus yielding delayed replicas $W'[1 \leq i \leq L] \cdot X[n-i]$. After photodetection, the replicas are summed as

$$Y[n] = \sum_{i=1}^{R} W'[R-i+1] \cdot X[n-i] = (W * X)[n]$$

(1)

where each symbol $Y[n]$ within the range of $[R+1, L+1]$ denotes the dot product between $W$ and a sliding window $[n-R, n-R+1, n-R+2, \ldots, n-1]$ of $X$, thus achieving convolution operations between the input and weight vectors.

The output waveform $Y$ contains $R+L-1$ symbols, amongst which $R-L+1$ symbols denote the convolution results, for each computing cycle. Here, each symbol is the result of $R$ multiplications and $R$ accumulation operations. As such, the computing speed can be given as $(R+L-1)/(R-L+1) \times 2 \times R \times B$, where $B$ denotes the symbol rate. For practical applications, the length of the input data vector is much larger than that of the weight vector ($L >> R$), thus $(R+L-1)/(R-L+1) \approx 1$ and the computing speed can be given as $2 \times R \times B$.

In addition, the same hardware architecture can be tailored to achieve matrix multiplication for the fully connected layer. Assuming that the input data vector $X_{FC}[n]$ and the weight vector $W_{FC}[R-i+1]$ both have a length of $R$ ($1 \leq i \leq R, 1 \leq n \leq R$), thus, according to Equation 1, the output waveform after photodetection is

$$Y_{FC}[n] = \sum_{i=1}^{R} W_{FC}[R-i+1] \cdot X_{FC}[n-i]$$

(2)

By sampling at the time slot denoted by $n = R+1$, the matrix multiplication result of the two input vectors is obtained as

$$Y_{FC}[R+1] = \sum_{i=1}^{R} W_{FC}[R-i+1] \cdot X_{FC}[R+1-i]$$

$$= \sum_{i=1}^{R} W_{FC}[i] \cdot X_{FC}[i]$$

(3)

The output waveform $Y$ contains $2L-1$ symbols for each computing cycle, amongst which only one symbol denotes the vector multiplication result from L multiplications and L accumulation operations. As such, the computing speed can be given as $1/(2L+1) \times 2 \times L \times B \approx B$.

As illustrated above, this time wavelength interleaving method can significantly enhance the computing power with WDM and a single modulator, albeit it is applicable only for specific convolution operations, rather than general matrix operations. Fig. 7 shows the experimental results for an 11 Tera-Ops convolutional accelerator processing large scale $500 \times 500$ pixel facial images.

The convolution accelerator can also be used to form convolutional neural networks (Fig. 8), which has shown unprecedented performance for image recognition applications. Here, we present the results of human image processing, using the convolutional accelerator as illustrated in [54]. Here, 90 comb lines were employed to form ten $3 \times 3$ convolutional kernels,
achieving diverse image processing functions, including: identical, blur, bottom/top/left/right Sobel, emboss, outline, sharpen and motion blur. A 500 × 500 input image was flattened into a vector and converted into an electrical input waveform via a high-speed electrical digital-to-analog converter, at a data rate of 62.9 Giga Baud. The waveform was then broadcast onto all wavelength channels and weighted via electro-optical modulation. Following this, the weighted replicas were transmitted through ∼2.2 km of standard single mode fibre (dispersion ∼17 ps/nm/km), which corresponds to a progressive delay of
Fig. 8. The operation principle of the photonic convolution accelerator for the convolutional layer with $R = 4$ and $L = 13$, and the fully connected layer with $R = L = 4$, consisting of an electro-optical modulator (EOM), an optical buffer that has progressive wavelength-sensitive delay, and an optical-to-electrical conversion module (O/E). Figures are adapted from [54].

15.9 ps that matches with the symbol rate. The wavelength channels were then de-multiplexed into 10 sub-bands that corresponded to the 10 convolutional kernels, and finally summed upon photodetection. The output waveforms were finally sampled and rescaled to form the feature maps, denoting a diverse range of pre-defined hierarchical features of the input image. In combination with a fully connected layer, the convolutional accelerators can be used to form convolutional neural networks, where the kernels’ weights are trained for specific tasks/datasets such as facial recognition.

V. DISCUSSIONS

While ONNs show great potential in achieving high computing power and energy efficiency, their inherent analog framework indicates that ultimately, hybrid opto-electronic neuromorphic hardware is a likely optimal solution that takes advantage of both the broadband optics and the versatility of digital electronics, where optics undertakes the majority of the computing operations and electronics manages the data flow and storage. In such architectures, particularly for deep learning networks with many internal hidden layers, optical computing units will be iteratively introduced, linked by electronics, to perform certain computing functions for each network layer, while electronics will likely still be needed to manage the overall network logistics, including the structure of the network, linking the hidden layers, and the data/parameter flow. Having said this, though, we note that there is still significant room to increase the range of functions performed optically, that currently tend to be done using electronics. These include the pooling layer as well as the output nonlinearity.

So far, although notable progress has been made on ONNs, many challenges still exist that need to be addressed for future applications. First, dense integration of the entire photonics system needs to be achieved, as this is the key to achieve competitive computing parallelism for ONNs in comparison to their electrical counterparts. Ultimately achieving computing with millions of parameters — sufficient for all practical applications — remains challenging for ONNs based on SDM or WDM, since the parameters need to be mapped onto physical divisions. TDM techniques can potentially address these needs, as the parameters are mapped onto temporal waveforms that theoretically can have infinite lengths, such as convolving vectors with a length of 0.25 million using TDM. [54] For WDM methods, architectures have been proposed [54] that are able to scale up to 25000 synapses using standard off-the-shelf telecommunications equipment.

In parallel, hybrid integration techniques, capable of integrating the comb source and subsequent components, including in particular spectral shapers (utilizing high-resolution wavelength demultiplexers and arrays of amplitude/phase controlling units achieved via either passive or active components), are necessary to make optimal use of optics’ broad bandwidths with WDM techniques.

Secondly, more categories of computing operations (such as the nonlinear functions of neurons and Fourier transforms) and network architectures (such as graph neural networks [158]) need to be demonstrated on chip to further enhance the universality of ONNs for diverse machine learning tasks. This will rely on advances in both novel computing architectures tailored to specific operations and the integration of high-nonlinearity components that can realize the nonlinear functions with relatively low optical power.

Thirdly, as ONNs will be achieved as assemblies of massive programmable photonic units for a high spatial-division parallelism, tailored algorithms to overcome the challenges of fabrication imperfections and on-chip cross-talk are necessary.
for fast-converging control of on-chip elements and training of the networks.

Finally, the unique advantages of optics, especially in terms of its compatibility with general optical devices such as cameras [159] or gratings [160] for image processing, should be investigated to further boost ONNs’ performance for these applications. Since these architectures avoid the need of digital electronics at the front end (for data format conversion such as electrical-to-optical and analog-to-digital), the power consumption can be greatly reduced.

With these challenges being fully addressed, ONNs can then be plugged into existing electronic hardware to significantly enhance the computing performance of the whole system, dramatically accelerating the training speed of computationally intense neural networks, and thus in turn potentially lead to more complicated and intelligent networks for advanced machine learning tasks such as fully automated vehicles and real-time image/video processing.

VI. CONCLUSION

We have reviewed recent advances in WDM-based ONNs, focusing on methods that use integrated microcombs to implement ONNs. We present results for human image processing using an optical convolution accelerator operating at 11 Tera operations per second. The open challenges and limitations of ONNs that need to be addressed for future applications are also discussed.

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