Advanced Applications for Kerr Micro-combs

David J. Moss

Optical Sciences Centre, Swinburne University of Technology, Hawthorn, VIC, Australia;
* Email: dmoss@swin.edu.au

***Abstract*— We present our latest results for advanced applications of optical Kerr frequency microcombs, including an optical convolutional accelerator operating at 11 Tera-OPS, as well as real-time video signal processing at a speed of 17 Terabits/s.**

Keywords—Kerr microcombs, signal processing, solitons

Integrated optical microcombs have become a hugely successful field in the past 15 years. [1- 4] Here, we present our work on ultrahigh bandwidth applications of Kerr microcombs, [5-24] including optical neural networks, [5,6] optical fiber data transmission, [7] and an optical real-time video digital signal processor operating at 18 Terabits/s. [8, 9]

Optical neural networks (ONNs) [5] are promising next-generation neuromorphic computers for ultra-high computing speeds enabled by the >10 THz wide telecom band. While Significant progress has been made in highly parallel, high-speed and trainable ONNs, processing large-scale data, needed for computer vision tasks, remains challenging because ONNs are fully connected structures with their input scale determined by hardware parallelism. This leads to tradeoffs in network scale and footprint. By interleaving wavelength, temporal, and spatial dimensions with an integrated Kerr microcomb, we demonstrate an optical convolution accelerator at 11.322 Tera-OPS/s (TOPS) and use it to process 250,000 pixel images with 10 convolution kernels at 3.8 TOPs. Our convolution accelerator (CA) is dynamically reconfigurable and scalable, serving as both a CA front-end as well as an optically deep CNN with fully connected neurons, with the same hardware. We use the deep CNN to achieve recognition of the full ten handwritten digits (0-9) with an accuracy of 88%. Our accelerator is stand alone and universal — fully compatible with electrical and optical interfaces, as a universal ultrahigh bandwidth data compressing front end for neuromorphic hardware bringing massive-data machine learning for real-time ultrahigh bandwidth data within reach.

We also demonstrate an optical real-time signal processor [8, 9] for digital video images that is reconfigurable, is based on components that are either integrated or compatible with integration, and operates at ultra-high bandwidths of 17-18 Terabits/s. This is sufficient to process almost 400,000 (399,061) video signals concurrently and in real-time, with up to 34 functions simultaneously. The system is equivalent to electrical digital signal processing (DSP) systems but performs at multi-terabit/s bandwidths, enabled by massively parallel processing. It is also very general, flexible, and highly reconfigurable – able to perform a wide range of functions without requiring any change in hardware. We perform multiple image processing functions in real-time, which is essential for machine vision and microscopy for tasks such as object recognition or identification, feature capture, and data compression. These functions include edge enhancement, edge detection, and motion blur correction. Edge enhancement and detection are key approaches to object recognition that rely on the detection of edges, or discontinuities in image brightness, texture, colour, or other properties. The processes that we employ to perform these functions include Hilbert transforms and differentiation for object edge enhancement and detection, and include both integral order and a continuous range of fractional order transforms, as well as image integration for motion blur. We demonstrate operation with 34 different functions, although the range of different functions is in fact unlimited given that the system can process a continuous range of arbitrary order functions, including fractional-order to high order differentiation. Our system uses an integrated Kerr microcomb source that generates 95 discrete taps, or wavelengths as the

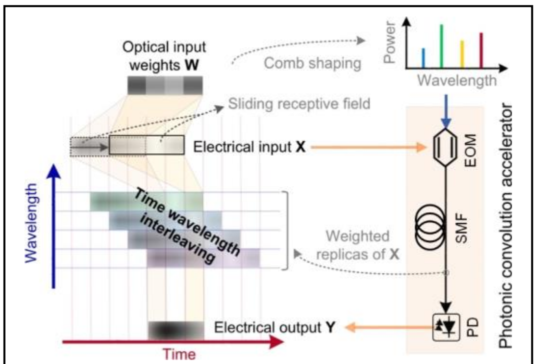

Figure 1 | Tera-OPS photonic convolution accelerator. EOM: electro-optical Mach-Zehnder modulator. SMF: standard single mode fibre. PD: photodetector.

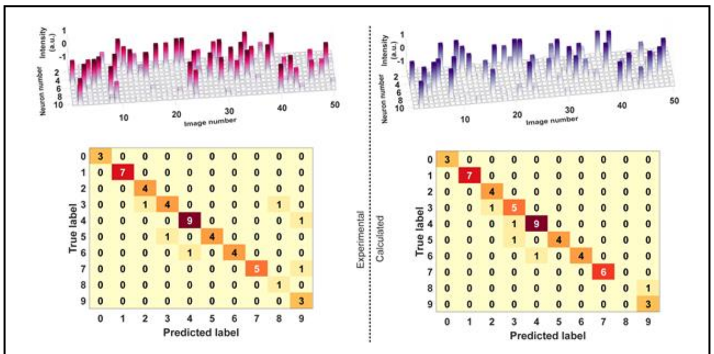

Figure 2 | Experimental and theoretical results for image recognition. Upper figures are sampled intensities of ten output neurons of the fully connected layer; lower figures are the confusion matrices.

basis for massively parallel processing, with single channel rates at 64 GigaBaud (pixels/s). The experimental results agree well with the theory, demonstrating that the processor is a powerful approach for ultrahigh-speed video image processing for robotic vision, machine learning, and many other emerging applications.

Figure 1 shows the operation principle of the photonic matrix convolutional accelerator (CA). The input data vector X is encoded as the intensity of temporal symbols in a serial electrical waveform at a symbol rate $1/\tau$ (baud), where τ is the symbol period. The convolution kernel is represented by a weight vector W of length R that is encoded in the optical power of the microcomb lines through spectral shaping performed by a Waveshaper. The temporal waveform X is multi-cast onto the kernel wavelength channels via electro-optical modulation, generating replicas weighted by W. Next the optical waveform is transmitted through a dispersive delay with a delay step (between wavelengths) equal to the symbol duration of X, achieving time and wavelength interleaving. Finally, the delayed and weighted replicas are summed via high speed photodetection so that each time slot yields a convolution between X and W for a given convolution window, or receptive field. The convolution window effectively slides at the modulation speed matching the baud rate of X. Each output symbol is the result of R multiply-and-accumulate operations, with the computing speed given by $2R/\tau$ OPS. Since the speed of this process scales with both the baud rate and number of wavelengths, it can be dramatically boosted into the TOP regime with the massively parallel wavelength channels of the microcomb source. The length of the input data X is unlimited so that the convolution accelerator can process data with an arbitrarily large scale—the only limitation being the capability of the external electronics and the number of wavelengths (for speed). The optical CNN fully connected layer had ten neurons, each corresponding to one of the ten categories of handwritten digits from 0 to 9, with the synaptic weights represented by a 72×10 weight matrix $\mathbf{W}_{FC}^{(l)}$ (ie., ten 72×1 column vectors) for the lth neuron ($l \in [1, 10]$) – with the number of comb lines (72) matching the length of the flattened feature map vector $\mathbf{X}_{FC}$. The shaped optical spectrum at the lth port had an optical power distribution proportional to the weight vector $\mathbf{W}_{FC}^{(l)}$, thus serving as the equivalent optical input of the lth neuron. After being multicast onto the 72 wavelengths and progressively delayed, the optical signal was weighted and demultiplexed with a single Waveshaper into 10 spatial output ports — each corresponding to a neuron. The final output of the optical CNN was represented by the intensities of the output neurons, where the highest intensity for each tested image corresponded to the predicted category. Supervised network training was performed offline electronically. We tested 500 8-bit 30 × 30 resolution images of the handwritten digit dataset with the deep optical CNN, achieving an accuracy of 88%. Figure 2 shows the resulting confusion matrices (theoretical and experimental). We present different architectures both to increase the speed to the PetaOP regime as well as increase the network size to more than 25,000 synapses in order to tackle larger challenges and to increase the accuracy to be closer to that of electronic chips – greater than 99%.

In summary, we demonstrate advanced applications of optical Kerr microcombs including an optical convolutional accelerator operating at 11.3 TOPS, an optical convolutional neural network to achieve recognition of handwritten digit images, and a real-time video image signal processor operating at 17 Terabits/s.

References

[1] A. Pasquazi et al., "Micro-combs: A novel generation of optical sources," *Physics Reports* **729**, 1-81 (2018).

[2] A. L. Gaeta, M. Lipson, and T. J. Kippenberg, "Photonic-chip-based frequency combs," *Nature Photonics* **13**, 158-169 (2019).

[3] L. Razzari et al., "CMOS compatible integrated optical hyper-parametric oscillator", *Nature Photonics* **4,** 41-44 (2010).

[4] D.J.Moss et al., "New CMOS-compatible platforms based on silicon nitride and Hydex for nonlinear optics", *Nature Photon.***7**, (8), 597 (2013).

[5] X. Xu et al., "11 TOPs photonic convolutional accelerator for optical neural networks", *Nature* **589** 44-51 (2021).

[6] X. Xu et al.,"Photonic perceptron based on a Kerr microcomb for scalable high speed optical neural networks", Laser & Phot. Rev. **14** (8) 2000070 (2020).

[7] B. Corcoran *et al.*, "Ultra-dense optical data transmission over standard fiber with a single chip source", *Nature Communicationss* **11** 2568 (2020).

[8] Mengxi Tan et al., "18 Tb/s photonic digital signal processor for real-time video image processing", Research Square, 15 August (2022). DOI:10.21203/rs.3.rs-1775424/v1.

[9] D.J. Moss, "18 Terabit per second photonic digital signal processor for real time video image processing", OSF Preprints (2022, August 28). https://osf.io/j3q84/. DOI: 10.31219/osf.io/j3q84

[10] M. Tan et al., "RF and microwave photonic temporal signal processing with Kerr micro-combs", Advances in Physics: X **6** (1), 1838946 (2021).

[11] J. Wu et al., "RF Photonics: An Optical Microcombs' Perspective," IEEE J. Sel. Top. Quantum Electron. **24**, no. 4, 6101020, Jul-Aug. (2018).

[12] Y. Sun, J. Wu, M. Tan, X. Xu, Y. Li, R. Morandotti, A. Mitchell, and D. J. Moss, "Applications of optical micro-combs", Advances in Optics and Photonics **15** (1) 86-175 (2023). https://doi.org/10.1364/AOP.470264.

[13] Mengxi Tan, X. Xu, J. Wu, A. Boes, B. Corcoran, T. G. Nguyen, S. T. Chu, B. E. Little, R. Morandotti, A. Mitchell, and David J. Moss, "Advanced applications of Kerr mircocombs", Proc. SPIE 11775, Integrated Optics: Design, Devices, Systems and Applications VI, 1177504; Integrated Optics Conference, SPIE Optics and Optoelectronics Symposium, April 19 - 22 (2021), Prague, Czech Republic. doi.org/10.1117/12.2588733.

[14] F. F. Liu, et al., "Compact optical temporal differentiator based on silicon microring resonator", Opt. Express 16, 15880-15886 (2008).

[15] Moss, D., "Accuracy of Photonic RF Transversal Signal Processors based on Microcomb", Research Square (2023). DOI: 10.21203/rs.3.rs-2505203/v2

[16] A. Cutrona et al, "Stability Properties of Laser Cavity-Solitons for Metrological Applications", ***Applied Physics Letters*** **122** 000000 (2023); doi: 10.1063/5.0134147.

[17] Yunping Bai, Xingyuan Xu,1, Mengxi Tan, Yang Sun, Yang Li, Jiayang Wu, Roberto Morandotti, Arnan Mitchell, Kun Xu, and David J. Moss, "Photonic multiplexing techniques for neuromorphic computing", ***Nanophotonics*** **12** (5): 795–817 (2023). DOI:10.1515/nanoph-2022-0485.

[18] Xingyuan Xu, Weiwei Han, Mengxi Tan, Yang Sun, Yang Li, Jiayang Wu, Roberto Morandotti, Arnan Mitchell, Kun Xu, and David J. Moss, "Neuromorphic computing based on wavelength-division multiplexing", ***IEEE Journal of Selected Topics in Quantum Electronics*** **29** (2) 7400112 (2023). DOI:10.1109/JSTQE.2022.3203159.

[19] Antonio Cutrona, Maxwell Rowley, Debayan Das, Luana Olivieri, Luke Peters, Sai T. Chu, Brent L. Little, Roberto Morandotti, David J. Moss, Juan Sebastian Totero Gongora, Marco Peccianti, Alessia Pasquazi, "High Conversion Efficiency in Laser Cavity-Soliton Microcombs", ***Optics Express*** Vol. 30, Issue 22, pp. 39816-39825 (2022).

[20] Maxwell Rowley, Pierre-Henry Hanzard, Antonio Cutrona, Hualong Bao, Sai T. Chu, Brent E. Little, Roberto Morandotti, David J. Moss, Gian-Luca Oppo, Juan Sebastian Totero Gongora, Marco Peccianti and Alessia Pasquazi, "Self-emergence of robust solitons in a micro-cavity", ***Nature*** **608** (7922) 303 – 309 (2022).

[21] Mengxi Tan, Xingyuan Xu, Jiayang Wu, Bill Corcoran, Andreas Boes, Thach G. Nguyen, Sai T. Chu, Brent E. Little, Roberto Morandotti, Arnan Mitchell, and David J. Moss, "Integral order photonic RF signal processors based on a soliton crystal micro-comb source", ***IOP Journal of Optics*** **23** (11) 125701 (2021).

[22] Mengxi Tan, Xingyuan Xu, Jiayang Wu, Bill Corcoran, Andreas Boes, Thach G. Nguyen, Sai T. Chu, Brent E. Little, Roberto Morandotti, Arthur Lowery, Arnan Mitchell, and David J. Moss, ""Highly Versatile Broadband RF Photonic Fractional Hilbert Transformer Based on a Kerr Soliton Crystal Microcomb", Invited Paper, Special Issue on MWP Meeting, ***Journal of Lightwave Technology*** **39** (24) 7581-7587 (2021).

[23] Mengxi Tan, X. Xu, J. Wu, T. G. Nguyen, S. T. Chu, B. E. Little, R. Morandotti, A. Mitchell, and David J. Moss, "Orthogonally polarized Photonic Radio Frequency single sideband generation with integrated micro-ring resonators", IOP ***Journal of Semiconductors*** **42** (4), 041305 (2021).

[24] Mengxi Tan, X. Xu, J. Wu, T. G. Nguyen, S. T. Chu, B. E. Little, R. Morandotti, A. Mitchell, and David J. Moss, "Photonic Radio Frequency Channelizers based on Kerr Optical Micro-combs", IOP ***Journal of Semiconductors*** **42** (4), 041302 (2021).