Neuromorphic Photonics for Intelligent Signal Processing

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***Abstract*— Neuromorphic photonic processors create a radically new hardware platform for intelligent signal processing by offering sub-nanosecond latency and high bandwidth with low energy. Here, we discuss the current development of neuromorphic photonics and its applications in real-time processing of multichannel, ultrafast signals.**

Keywords—neuromorphic computing, silicon photonics, machine learning, signal processing.

I. Introduction

State-of-the-art AI algorithms, by and large, are implemented using neural networks, a computational architecture inspired by the neuro-synaptic architecture of the brain [1]. Today, practically all AI algorithms operate on digital computers built on von Neumann architecture, a computing architecture that has dominated computing design since its invention. However, neural network models vary significantly from von Neumann model in that neural networks are highly parallel and distributed, while von Neumann design is essentially sequential (or, in the best case: sequential-parallel with multi-processors). The stark difference between the two architectures reduces computation performance and increases power consumption. As a result, most programs operating on standard computers, such as face and voice recognition, image processing, and so on, are confined to kilohertz or megahertz rates.

Many new applications nowadays need neural networks to deliver gigahertz bandwidth and low-latency computing. Real-time control for robots and driverless vehicles, intelligent signal processing for wideband signals such as radio-frequency and optical communication signals, and so on are examples of applications[2]–[5]. Many efforts are devoted to the development of new machine learning algorithms that optimize between performance and computational complexity (in order to make the algorithms implementable on digital hardware, e.g., application-specific integrated circuits (ASIC).) Nonetheless, the advantages of machine learning algorithms are generally validated using traditional computers and tested offline. Due to the tight requirements in these applications for high throughput, low energy, and low latency, implementation of machine learning algorithms in real-time remains a major challenge.

Neuromorphic (i.e. neuron isomorphic) photonics[6]–[10] promises to tackle these challenges by developing radical new hardware platforms capable of emulating the neural structure of the brain using photonic devices and waveguides. Photonics has unrivaled capabilities for interconnects and communication that may overcome the bandwidth and interconnectivity trade-offs that electronics essentially suffers from. As a consequence, algorithms operating on neuromorphic photonic hardware may be able to overcome electronic performance bottlenecks and gain advantages in terms of speed, latency, and power consumption while addressing intellectual tasks that are now unattainable by digital electronic platforms. In this talk, we will discuss the current development neuromorphic photonics hardware [8]–[11][12][13] and review its applications for intelligent signal processing [2], [3], [5], [7], an application domain where high speed, sub-nanosecond latencies, and energy efficiency trump the sheer size of processor. (Most neuromorphic photonic hardware will be smaller (hundreds of neurons) than electronic implementations (tens of millions of neurons). In these applications 1) the same operation must be performed repeatedly and rapidly; 2) the signals to be processed are already in the analog domain; and 3) the same hardware may be employed in a reconfigurable manner. We aim to provide an intuitive understanding of neuromorphic photonics of why, where, and how photonic neural networks can play a unique role in enabling new domains of applications.

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