Spiking Neural Network Equalization: Towards Evaluation of Throughput and Power Consumption

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Abstract *Recent work has reported on the excellent performance of spiking neural networks (SNN) for signal processing in optical transceivers. In this work, we discuss the challenges of evaluating SNN throughput and power consumption, present first results, and discuss future steps.*

Introduction

To sustain the exponential growth of data center traffic, optical transceivers need to evolve towards higher rates, smaller footprint and lower power consumption, at the same time. To achieve these challenging goals, recent research envisions moving parts of digital signal processing (DSP) to analog frontends with lower power consumption.

Photonic neuromorphic computing[1] has been proposed, e.g., for fiber non-linearity compensation[2], as well as for chromatic dispersion (CD) compensation and nonlinear equalization in short-reach optical transmission[3]–[5].

Also, a return to analog adaptive equalizers has gained traction, e.g., in[6], the transmitter DSP feeds two electrical non-return-to-zero (NRZ) signals to an analog pulse-amplitude-modulation 4-level (PAM-4) encoder, whose output is filtered by a continuous time linear equalizer (CTLE) and a 3-tap feed forward equalizer (FFE). In[7], analog finite impulse response (FIR) filters are used to adaptively equalize an NRZ signal.

At the same time, the research community aims for implementing more powerful algorithms, e.g. based on artificial intelligence (AI) techniques, on analog electronics. An important subfield is in-memory-computing (IMC)[8], which aims for efficient calculation of vector-matrix multiplications. Research on IMC is mainly driven by the urgent need of AI accelerators for making inference by artificial neural networks (ANNs) more power-efficient. Analog electronic neuromorphic computing offers a disruptive path towards AI-based signal processing. Imitating the functioning of the human brain, spiking neural networks (SNNs)[9] in analog hardware[10] combine IMC with sparse representation of information by spiking signals. Several startup companies are currently commercializing SNNs on neuromorphic hardware, mainly in the area of low power sensors.

SNN Equalization: Performance

Our aim is to evaluate the SNN technology as enabler for reducing footprint and power consumption of optical transceivers. In[11], we show by simulation in the Norse software[12] that SNNs allow for competitive nonlinear detection of PAM4 signals in IM/DD links. Similar results are reported in[13],[14]. In the follow-up works[15],[16] we show that the detection capability of SNNs is preserved when they are executed on the analog neuromorphic BrainScaleS-2 (BSS-2) hardware platform[10] by using `hxtorch.snn`[17]. Finally, in[18], we report an optical transmission experiment with succesful SNN detection in offline processing.

SNN Equalization: Throughput and Power Consumption

The existing results show the algorithmic suitability of SNNs. The challenge is now to evaluate (Q1) whether SNNs can meet the throughput requirements, and (Q2) whether they provide the promised power savings.

The successful realization in analog hardware as reported in[15],[16] only provides limited answers to the questions Q1 and Q2. The BSS-2 application-specific integrated circuit (ASIC) provides a neuromorphic platform for a wide range of applications and with a rich periphery for monitoring, training, and deployment of new SNN models. Consequently, the circuitry is highly configurable and designed for flexibility rather then efficiency, the throughput is slowed down, and control and monitoring signals contribute significantly to the power consumption.

In this presentation, we discuss the key challenges in assessing the potential of the SNN technology in terms of throughput and power consumption. We present first results and discuss future steps.

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