Spiking Neural Network Equalization for IM/DD Optical Communication

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Abstract

A spiking neural network (SNN) equalizer model suitable for electronic neuromorphic hardware is designed for an IM/DD link. The SNN achieves the same bit-error-rate as an artificial neural network, outperforming linear equalization.

1 Introduction

Low cost and low power optical transceivers are indispensable for supporting the exponentially growing data center traffic caused by cloud-based services. The high power consumption of digital signal processing (DSP) has motivated research on moving parts of the receiver DSP to an analog lower power frontend. For instance, photonic neuromorphic computing \(^1\) has been studied recently, e.g., for compensating for chromatic dispersion (CD) and nonlinear impairments in short reach optical transmission \(^2\), \(^3\). An alternative solution is analog electronic neuromorphic computing, implementing SNNs \(^4\) in analog hardware \(^5\) by mimicking the basic operation principles of the human brain, thereby adopting the brain’s unchallenged power efficiency. SNNs are applied in \(^6\) for an inference task on a spectrogram in fiber-optic distributed acoustic sensing. Recently, in-the-loop training of SNNs on analog hardware has achieved state-of-the-art performance in inference tasks \(^7\). Despite electronics operating slower than photonics, electronic hardware enables higher scalability and thus greater throughput through parallelization, making it a suitable choice for energy-efficient signal processing. An important aspect to be analyzed is whether SNNs in analog electronic hardware support the accuracy required by communication systems.

To assess the accuracy of SNNs, we design equalization and demapping using SNNs suitable for a hardware implementation on the BrainScaleS-2 (BSS-2) system \(^5\). We evaluate our SNN in a software simulation for the detection of a 4-level pulse amplitude modulation (PAM4) signal for an intensity modulation/direct detection (IM/DD) link, impaired by CD and additive white Gaussian noise (AWGN). Our SNN achieves the bit error rate (BER) of an artificial neural network (ANN), outperforming a digital linear minimum mean square error (LMMSE) equalizer.

2 Equalization and Demapping using Spiking Neural Networks

For equalization and demapping, we consider an SNN with a single hidden layer, consisting of 40 spiking leaky-integrate and fire (LIF) neurons \(^4\), Sec. 1.3\(^1\), and an output layer constituted by four non-spiking leaky-integrate (LI) \(^4\), Sec. 1.3\(^1\) readout neurons. This architecture fits in size on the BSS-2 system \(^5\). Each LIF neuron \(j\) maintains an internal membrane state \(v_j\) described by the
ordinary differential equations

\[ \tau_m \dot{v}_j(\tau) = -(v_j(\tau) - v_{\text{leak}}) + I_j(\tau) \quad \text{with} \quad I_j(\tau) = \sum_{i=0}^{N-1} \sum_{s \in \text{spikes } i\text{-th neuron}} W_{ji} \Theta(\tau - \tau_s^i) \exp\left(\frac{\tau - \tau_s^i}{\tau_{\text{syn}}}\right), \] (1)

integrating synaptic input \( I \), caused by pre-synaptic events \( \tau_s^i \), onto its membrane. As the membrane potential exceeds a threshold \( \vartheta \), the neuron emits a post-synaptic spike a time \( \tau_s^j \), after which it is set to a reset potential \( v_r \). LIF neurons exhibit the same dynamics, without the ability to spike. The parameters \( \tau_{\text{syn}} \) and \( \tau_m \) are the time constants of the synaptic current and the membrane potential, respectively.

A received sample \( y_t \) and its \( \lfloor n_{\text{tap}}/2 \rfloor \) predecessors and successors (\( n_{\text{tap}} \) odd) are translated to 10 input spike events per sample by a spike encoder (see Fig. 1), potentially replacing power-hungry analog-to-digital conversion (ADC) in hardware. To this end, each input neuron emits a spike at time \( \tau_s^i \) given by the scaled log-distance [8] to a reference point \( \chi_i \), assigned to each input neuron. The input sample \( y_t \) gets classified with the label \( k \in \{0, 1, 2, 3\} \) of the output neuron with the maximum membrane value \( v_k(\tau) \) over the considered time frame. Hence, the network learns to place hidden spike events in time, such that the readout traces are adjusted appropriately.

For training our SNNs we rely on backpropagation through time (BPTT) with the Adam optimizer and surrogate gradients (SuperSpike [8]) to account for the discontinuity of spiking LIF neurons. Note that our simulations are implemented in hxtorch [9], also supporting execution on the BSS-2 system.

### 3 Results and Conclusions

In Fig. 2A, we display a simulated IM/DD link. Bits are mapped to a PAM4 constellation, the signal is upsampled and filtered by a root-raised-cosine (RRC). The signal is then shifted to the positive and CD is applied. At the receiver, a PD squares the signal and AWGN is added. The signal is then RRC filtered and downsampled. The resulting signal \( y \) is equalized and demapped. As reference, we use a digital 17 tap LMMSE equalizer, followed by a demapper with BER optimized decision boundaries, see Fig. 2D (right), and ANNs with one and two hidden layers, respectively, see Fig. 2C. In Fig. 2D (left) we see that joint equalization and demapping by a 17 tap SNN outperforms the LMMSE, and performs as well as the 17 tap ANN1, which has 1 hidden layer with 40 neurons, similar to the SNN. The reference schemes and the SNN were trained using supervised learning. By means of software simulation, we have shown that an SNN suitable for analog electronic hardware can efficiently compensate impairments in a simulated...
IM/DD link. In ongoing research, we implement the proposed SNN on the BSS-2 system, with the aim to reproduce the reported results on analog hardware.

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