Sub-mW Neuromorphic SNN audio processing applications with Rockpool and Xylo

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Abstract—Spiking Neural Networks (SNNs) provide an efficient computational mechanism for temporal signal processing, especially when coupled with low-power SNN inference ASICs. SNNs have been historically difficult to configure, lacking a general method for finding solutions for arbitrary tasks. In recent years, gradient-descent optimization methods have been applied to SNNs with increasing ease. SNNs and SNN inference processors therefore offer a good platform for commercial low-power signal processing in energy constrained environments without cloud dependencies. However, to date these methods have not been accessible to Machine Learning (ML) engineers in industry, requiring graduate-level training to successfully configure a single SNN application. Here we demonstrate a convenient high-level pipeline to design, train and deploy arbitrary temporal signal processing applications to sub-mW SNN inference hardware. We apply a new straightforward SNN architecture designed for temporal signal processing, using a pyramid of synaptic time constants to extract signal features at a range of temporal scales. We demonstrate this architecture on an ambient audio classification task, deployed to the Xylo SNN inference processor in streaming mode. Our application achieves high accuracy (98%) and low latency (100 ms) at low power (<100 µW dynamic inference power). Our approach makes training and deploying SNN applications available to ML engineers with general NN backgrounds, without requiring specific prior experience with spiking NNs. We intend for our approach to make Neuromorphic hardware and SNNs an attractive choice for commercial low-power and edge signal processing applications.

Index Terms—Audio processing, Spiking Neural Networks, Deep Learning, Neuromorphic Hardware, Python.

INTRODUCTION

Existing Deep Neural Network (DNN) approaches to temporal signal classification generally remove the time dimension from the data by buffering input windows over e.g. 40 ms and processing the entire window as a single frame [1], [2], or else apply models with complex recurrent dynamics such as Long Short-Term Memories (LSTMs) [3]. In contrast to Artificial Neural Networks (ANNs), Spiking Neural Networks (SNNs) include multiple temporally-evolving states with dynamics over a range of configurable time-scales. These dynamics can be applied in recurrent networks to form a complex temporal basis for extracting information from temporal signals, either through random projection [2], [4] or constructed with carefully chosen temporal properties [5].

Random recurrent architectures have historically been used for SNNs because they simplify the configuration problem — when only the readout layer is trained, configuration is performed by simply applying linear regression [4]. An alternative approach is to build feed-forward networks with individual spiking units tuned to a range of various frequencies, by selecting synaptic and membrane time constants [6]. Recent advances in optimization of SNNs using surrogate gradient descent [7], [8] have provided a feasible solution for configuring deep feedforward SNNs. However, most available libraries for simulating SNNs do not support gradient calculations, and are designed to simulate biological architectures rather than modern DNNs. At the same time, modern ML libraries for training DNNs do not support building or training SNNs.

We here demonstrate using a modern ML library for SNNs, “Rockpool” [9], coupled with a new SNN inference processor “Xylo”, to train and deploy a temporal signal classification task. Recently several alternative libraries for SNN-based training with Pytorch have emerged [10], [11]. However, these libraries do not support multiple computational backends for training, and do not support deployment to neuromorphic hardware.

AN AMBIENT AUDIO SCENE CLASSIFICATION TASK

Audio headsets, phones, hearing aids and other portable audio devices often use noise reduction or sound shaping to improve listening performance for the user. The parameters used for noise reduction may depend on the noise level and characteristics surrounding the device and user. For example, optimal noise filtering may differ depending on whether the user is in a quiet office environment, on a street with passing traffic, or in a busy cafe with surrounding conversation.

To choose from and steer pre-configured noise reduction approaches, we propose a low-power solution to automatically and continuously classify the noise environment surrounding the user. We train and deploy an SNN on a low-power neuromorphic inference processor to perform a continuous temporal signal monitoring application, with weak low-latency requirements (environments change on the scale of minutes), but hard low-energy requirements (portable audio devices are almost uniformly battery-powered).

We use the QUT-NOISE [12] background noise corpus to train and evaluate the application. QUT-NOISE consists of multiple sequential hours of ambient audio scene recordings, from which we used the CAFE, HOME, CAR and STREET classes.

This work was partially funded by the ECSEL Joint Undertaking (JU) under grant agreements number 876925, “ANDANTE” and number 826655, “TEMPO”. The JU receives support from the European Union’s Horizon 2020 research and innovation program and France, Belgium, Germany, Netherlands, Portugal, Spain, Switzerland.

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A TEMPORAL SIGNAL PROCESSING ARCHITECTURE FOR SNNs

We make use of slow synaptic and membrane states provided by leaky integrate-and-fire (LIF) spiking neurons to integrate information within an SNN. The dynamics of an LIF neuron are given by

\[
\begin{align*}
\dot{I}_{\text{syn}} \cdot \tau_{\text{mem}} &= -I_{\text{syn}} + z(t) \\
V_{\text{mem}} \cdot \tau_{\text{syn}} &= -V_{\text{mem}} + I_{\text{syn}} + b \\
V_{\text{mem}} > \theta &\rightarrow \begin{cases} 
\dot{z}(t) = z(t) + \delta(t - t_k) \\
V_{\text{mem}} = V_{\text{mem}} - \theta
\end{cases}
\end{align*}
\]

Here \(z(t)\) are weighted input events, \(I_{\text{syn}}\) and \(V_{\text{mem}}\) are synaptic and membrane state variables, and \(z(t)\) is the train of output spikes when \(V_{\text{mem}}\) crosses the threshold \(\theta\) at event times \(t_k\). The synaptic and membrane time constants \(\tau_{\text{syn}}\) and \(V_{\text{mem}}\) provide a way to sensitize the LIF neuron to a particular time-scale of information.

We use a range of pre-defined synaptic time constants in a deep SNN to extract and integrate temporal information over a range of scales, which can then be classified by a spiking readout layer. The proposed network architecture is shown in Figure 1.

Single-channel input audio is pre-processed through a filter-bank, which extracts the power in each frequency band, spanning 50 Hz to 8000 Hz over 16 logarithmically-spaced channels. Instantaneous power is temporally quantised to 1 ms bins, with amplitude encoded by up to 15 events per bin per channel.

Input signals are then processed by three spiking layers of 24 LIF spiking neurons in each layer, interposed with dense weight matrices. Each layer contains a fixed common \(\tau_{\text{mem}}\) of 2 ms, and a range of \(\tau_{\text{syn}}\) from 2 ms to 256 ms. The synaptic time constants are arranged in an increasing geometric series, such that early layers have only short \(\tau_{\text{syn}}\) while final layers contain the full range of \(\tau_{\text{syn}}\) values. The first layer contains neurons with two time constants of \(\tau_{\text{syn}} = 2\) and 4 ms. The final layer contains neurons with \(\tau_{\text{syn}} = 2, 4, 8, 16, 32, 64, 128\) and 256 ms.

The readout layer consists of four spiking neurons corresponding to the four classes of ambient audio.

No bias parameters were used in this network.

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Fig. 1. **Spiking network architecture for temporal signal processing.** A filter bank splits single-channel audio into sixteen channels, spanning 50Hz to 8000 Hz. The power in each frequency band is quantised to 4 bits, then injected into the SNN. The spiking network consists of three hidden layers, with a pyramid of time constants from slow to fast distributed over 24 neurons in each layer. Each layer contains several time constants, with the first hidden layer containing only short time constants (\(\tau_1, \tau_2\)), and the final hidden layer containing short to long time constants (\(\tau_1\) to \(\tau_8\)). Finally, the readout layer outputs a continuous one-hot event-coded prediction of the current ambient audio class.

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ROCKPOOL: AN OPEN-SOURCE PYTHON LIBRARY FOR TRAINING AND DEPLOYING DEEP SNNs

Rockpool [9] is a high-level machine-learning library for spiking NNs, designed with a familiar API similar to other industry-standard python-based NN libraries. The API is similar to PyTorch [13], and in fact PyTorch classes can be used seamlessly within Rockpool. Rockpool has the goal of making supervised training of an SNN as convenient and simple as training an ANN. The library interfaces with multiple backends for accelerated training and inference of SNNs, currently supporting PyTorch [13], Jax [14], Numpy, Brian 2 [15] and NEST [16], and is easily extensible. Rockpool enables hardware-aware training for neuromorphic processors, and provides a convenient interface for mapping, deployment and inference on SNN hardware from a high-level Python API.

Rockpool can be installed with “pip” and “conda”, and documentation is available from https://rockpool.ai. Rockpool is an open-source package, with public development based at https://github.com/synsense/rockpool.

DEFINING THE NETWORK ARCHITECTURE

The network architecture shown in Figure 1 is defined in a few lines of Python code, shown in Listing 1.

TRAINING APPROACH

We trained the SNN on segments of 1s duration using BPTT and surrogate gradient descent [7], [8]. We applied a mean-squared-error loss to the membrane potential of the readout neurons, with a high value for the target neuron \(V_{\text{mem}}\) and a low value for non-target neuron \(V_{\text{mem}}\). After training we set the threshold of the readout neurons such that the target neurons emit events for their target class and remain silent for non-target classes. Pytorch Lightning [17] was used to optimize the model against the training set using default optimization parameters.

XYLO DIGITAL SNN ARCHITECTURE

We deployed the trained model to a new digital SNN inference ASIC “Xylo”. Xylo is an all-digital spiking neural network ASIC, for efficient simulation of spiking leaky integrate-and-fire neurons with exponential input synapses. Xylo is highly optimised for inference on SNN hardware from a high-level Python API.
from rockpool.nn.combinators import Sequential
from rockpool.nn.modules import LinearTorch, LIFTorch
from rockpool.parameters import Constant

Nh = 24  # − Hidden layer size

# − Define pyramid of time constants over SNN layers
taus = [2**n * 1e-3 for n in range(1, 9)]
tau_layer1 = [taus[i] for i in range(2) for _ in range(Nh // 2)]
tau_layer2 = [taus[i] for i in range(4) for _ in range(Nh // 4)]
tau_layer3 = [taus[i] for i in range(8) for _ in range(Nh // 8)]

# − Define the network as a sequential list of modules
net = Sequential(
    LinearTorch((16, Nh)),  # − Linear weights, hidden layer 1
    LIFTorch(Nh, tau_syn=Constant(tau_layer1)),  # − LIF layer
    LinearTorch((Nh, Nh)),  # − Hidden layer 2
    LIFTorch(Nh, tau_syn=Constant(tau_layer2)),
    LinearTorch((Nh, Nh)),  # − Hidden layer 3
    LIFTorch(Nh, tau_syn=Constant(tau_layer3)),
    LinearTorch((Nh, Nh)),  # − Readout layer
    LIFTorch((8))
)

Listing 1. Define an SNN architecture in Rockpool. The network here corresponds to Fig 1.

Fig. 2. Architecture of the digital spiking neural network inference processor “Xylo”. Xylo supports 1000 digital LIF neurons, 16 input and 8 output channels. Recurrent weights with restricted fan-out of up to 32 targets per neuron can be used to map deep feed-forward networks to the Xylo architecture.

Rockpool includes a bit-accurate simulation of the Xylo architecture, “XyloSim”, fully integrated with the high-level Rockpool API.

Mapping and deployment to Xylo

Mapping: Rockpool provides full integration with Xylo-family hardware development kits (HDKs), supporting deployment of arbitrary network architectures to Xylo. The ability for Xylo to implement recurrent connectivity within the hidden population permits arbitrary network architectures to be deployed. Feedforward, recurrent and residual SNN architectures are all equally supported for deployment. This is accomplished by embedding feedforward network weights as sub-matrices within the recurrent weights of Xylo. Figure 4 illustrates this mapping for the network architecture of Figure 1.

The Python mapping interface xylo.mapper performs DRC checks to ensure that a given network is compatible with the Xylo architecture. The mapper then converts the LIF neuron models to Xylo neurons, and extracts the neuron parameters from the network. Hardware IDs are assigned to each neuron, and network weight parameters are placed into the required Xylo configuration locations.

Quantization: Floating-point parameter values must be converted to the integer representations on Xylo. For weights and thresholds, this is accomplished by considering all input weights to a neuron, then computing a scaling factor such that the maximum absolute weight is mapped to $\pm 128$, with the threshold scaled by the same factor, then rounding parameters to the nearest integer.

The deployment process is shown in Listing 3.

Results

The accuracy for the trained model is given in Table I. The quantized model was deployed to a Xylo HDK, and tested
on audio segments of 60 s duration. We observed a drop in accuracy of 0.8% from the training accuracy, and a drop of 0.7% due to model quantization.

We measured real-time power consumption of the Xylo ASIC running at 6.25 MHz while processing test samples (Table II). Audio pre-processing (“Filter bank” in Figure 1) was performed in simulation, while SNN inference was performed on the Xylo device. We observed an average total power consumption of 542 µW while performing the audio classification task. The idle power of the SNN inference core was 219 µW, with a dynamic inference cost of 93 µW. The IO power consumption used to transfer pre-processed audio to the SNN was 230 µW. Note that in a deployed application, audio pre-processing would be performed on device, with a concomitant reduction of IO power requirements.

Our model performs streaming classification of ambient audio with median latency of 100 ms. Figure 5 shows the response latency distribution, from onset of an audio sample until the first spike from the correct class output neuron.

Figure 6 shows several example audio samples classified by the trained network.

**Inference energy benchmarks:** Our network performs continuous non-frame-based inference, making a precise definition of “an inference” complicated. We considered two possible definitions for inference time: one based on the median latency (100 ms; Figure 5); and one based on the time taken to perform a full evaluation of the network (network time-step of 1 ms).

Based on the continuous power measurements in Table II, our system exhibits per-inference dynamic energy consumption of 9.3 µJ (med. latency) and 93 nJ (network time-step). Per-inference total energy consumption was 54.2 µJ (med. latency) and 542 nJ (network time-step). These results are summarised in Table III.

Recent work deploying a keyword-spotting application to low-power CNN inference hardware achieved total energy consumption of 251 µJ per inference on the optimised Maxim MAX78000 accelerator, and 11 2000 µJ per inference on a low-power microprocessor (ARM Cortex M4F) [18]. This corresponded to a continuous power consumption of 71.7 mW (MAX78000) and 12.4 mW (Cortex M4F) respectively.

Previous work benchmarking audio processing applications
We demonstrated a general approach for implementing audio processing applications using spiking neural networks, deployed to a low-power Neuromorphic SNN inference processor “Xylo”. Our solution reaches high accuracy (98 %) with <100 spiking neurons, operating in streaming mode with low latency (med. 100 ms) and at low power (<100 µW dynamic inference power). Xylo exhibits lower idle power, lower dynamic inference power and lower energy per inference than other low-power audio processing implementations.

Our software pipeline “Rockpool” (rockpool.ai) provides a modern Machine Learning approach to building applications, with a convenient high-level API for defining neural network architectures. Rockpool supports definition and training of SNNs via several automatic differentiation back-ends. Rockpool also supports quantization, mapping and deployment to SNN inference hardware in a few lines of Python.

Our approach supports commercial design and deployment of SNN applications, by making the configuration process of SNNs accessible to ML engineers without graduate-level training in SNNs.

Here we have not demonstrated the full capabilities of Rockpool, which also supports residual spiking architectures, quantization- and hardware-aware training, training for time constants and other neuron parameters, and high extensibility for additional computational back-ends.

We anticipate SNNs and low-power neuromorphic inference processors to contribute significantly to the current push for low-power machine learning at the edge.

REFERENCES

[1] G. Chen, C. Parada, and G. Heigold, “Small-footprint keyword spotting using deep neural networks,” in 2014 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), 2014, pp. 4087–4091.
[2] P. Blouw, X. Choo, E. Hunsberger, and C. Eliasmith, “Benchmarking keyword spotting efficiency on neuromorphic hardware,” in Proceedings of the 7th Annual Neuro-Inspired Computational Elements Workshop, ser. NIC’19. New York, NY, USA: Association for Computing Machinery, 2019. [Online]. Available: https://doi.org/10.1145/3320288.3320304
[3] J. Deng, B. Schuller, F. Eyben, D. Schuller, Z. Zhang, H. Francois, and E. Oh, “Exploiting time-frequency patterns with LSTM-RNNs for low-bitrate audio restoration,” Neural Computing and Applications, vol. 32, no. 4, pp. 1095–1107, Feb. 2020. [Online]. Available: https://doi.org/10.1007/s00521-019-04158-0
[4] W. Maass and H. Markram, “On the computational power of circuits of spiking neurons,” Journal of Computer and System Sciences, vol. 69, no. 4, pp. 593–616, 2004. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0022000004000406
[5] A. Voelker, I. Kajić, and C. Eliasmith, “Legendre memory units: Continuous-time representation in recurrent neural networks,” in Advances in Neural Information Processing Systems, H. Wallach, H. Larochelle, A. Beygelzimer, F. d’Alch`e-Buc, E. Fox, and R. Garnett, Eds., vol. 32. Curran Associates, Inc., 2019. [Online]. Available: https://proceedings.neurips.cc/paper/2019/file/752285b9f67a1be5a7a84932f2f05-Paper.pdf
[6] P. Weideli and S. Sheik, “Wavesense: Efficient temporal convolutions with spiking neural networks for keyword spotting,” 2021. [Online]. Available: https://arxiv.org/abs/2111.01456
[7] J. H. Lee, T. Delbruck, and M. Pfeiffer, “Training deep spiking neural networks using backpropagation,” Frontiers in Neuroscience, vol. 10, 2016. [Online]. Available: https://www.frontiersin.org/articles/10.3389/ fnins.2016.00508
[8] E. O. Nefci, H. Mostafa, and F. Zenke, “Surrogate gradient learning in spiking neural networks: Bringing the power of gradient-based optimization to spiking neural networks,” IEEE Signal Processing Magazine, vol. 36, no. 6, pp. 51–63, 2019.
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