Evolutionary Optimization for Spiking Neural Networks - Clustering of FMCW Radar data

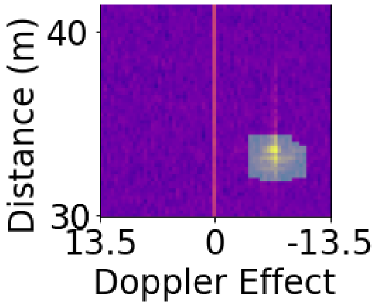

Fig. 1: FMCW range-doppler map with cluster. [1]

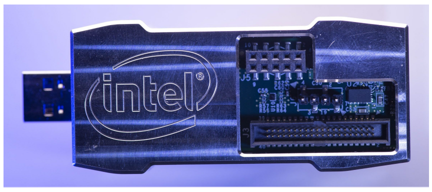

Fig. 2: Intels neuromorphic stick Kapoho Bay. [2]

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Background

For the past decade, artificial neural networks (ANNs) have been dominating many research areas, due to the success of optimizing a network using backpropagation together with large amounts of data for various applications. Spiking neural networks (SNNs), on the other hand, are more biologically plausible networks than ANNs [3], with a concept similar to that of a biological neuron. Unlike ANNs, these networks process data asynchronously and sparsely, namely through so called spikes. This potentially leads to highly efficient networks with a reduced energy consumption compared to ANNs up to a power of ten when implemented on specialized *neuromorphic hardware* [4].

These networks are, however, significantly harder to construct and train than ANNs. The reason for that is the non-differentiability of the binary spikes that these networks communicate with. This makes it impossible to use widely established training methods from ANNs like backpropagation. Although several alternatives have been proposed in recent years, there is still a lot of potential in designing and training an network of spiking neurons in order to perform optimally on a certain task.

One solution to this problem might be evolutionary optimization [5]. This, rather informed way of doing grid search, is a biologically plausible training and optimization method. Recent studies have already demonstrated its effectiveness on optimizing SNNs (for neuromorphic hardware) [6], [7].

Task Description

Throughout this project you will be working together with several colleagues from our neuromorphic computing group on implementing an evolutionary optimization framework for SNNs. We plan to collaboratively develop a complete framework able to optimize not only the parameters of a spiking network, such as the synaptic weights, but also the whole architecture, i.e. the connections between neurons, for different applications.

Your part of the project will be to first identify suitable evolutionary optimization approaches from the literature. You will then design a modular, parallel concept for implementing the system. Finally you will evaluate the clustering performance of the evolutionary optimization algorithm on range-doppler maps collected from an FMCW radar (see Fig. 1). For the evaluation, we will provide you with an existing spiking clustering algorithm as a reference and benchmark.

During this project you will be

- doing an extensive literature research, specifically on evolutionary optimization,
- designing a modular concept for a new evolutionary optimization framework,
- implementing the framework in a parallel and efficient way,
- evaluating/benchmarking the system on real-world radar data and documenting your

References

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