Applications of Spiking Neural Networks

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We are pleased to introduce this issue of Information Processing Letters presenting state-of-the-art articles on Applications of Spiking Neural Networks. Spiking neural networks are a class of neural networks that is increasingly receiving attention as both a computationally powerful and biologically more plausible model of distributed computation. Much work so far has focused on fundamental issues like computational complexity, biologically plausible models, effects of biological learning rules and such.

In this issue, there are five articles that consider how spiking neural networks can be used towards applications. We will discuss them in turn.

One intriguing proposal for how to make use of networks of spiking neurons has been the *Liquid State Machine*, by Maass, Natschläger & Markram [3]. Maass et al. realized that a randomly connected network of spiking neurons effectively implements a complex temporal filter through the intricacies of reverberating activity and synaptic dynamics. Given a temporally extended input, like speech, the collective activity of the network can be described as a trajectory through a high-dimensional state space, and this trajectory should be identifiably specific for the input at hand. A simple "read-out" decoder should then be sufficient to classify the temporal pattern.

In the paper "Isolated Word Recognition With The *Liquid State Machine*: A Case Study", Verstraeten, Schrauwen, Stroobandt and Van Campenhout study speech recognition in the Liquid State Machine (LSM). For a standard vocabulary set, they test a variety of temporal encodings that are fed into an LSM, and a subsequent simple linear decoder classifies each particular pattern. Surprisingly, Verstraeten et al. only find (encouragingly good) performance for the LSM when the encoding back-end approximates the encoding scheme of the inner ear.

Learning rules equivalent to those employed in traditional sigmoidal neural networks have also been derived for (layered) spiking neural networks, for example a gradient based error-backpropagation rule like *Spikeprop* [1]. With such a learning rule, it was shown that spiking neural network can in practice compute non-linearly seperable functions like traditional neural networks.

Booij & Nguyen present learning rule based on error-backpropagation that eliminates important limitations of the *Spikeprop* rule in the paper entitled "A gradient descent rule for spiking neurons emitting multiple spikes". Most importantly, in their derivation the error gradient is computed for a neuron emitting multiple spikes. Additionally, simple heuristics are discussed that diminish the disruptive effect of discontinuities in the membrane potential for gradient descent algorithms. The effectiveness of the improved algorithm is demonstrated on a temporal version of the classical XOR problem, and on the classification of Poisson spike trains. Interestingly, for the simplest XOR problem Booij & Nguyen show that there is a "hair trigger" solution in a network without hidden layer.

Another area where spiking neurons are thought to be especially powerful is that of *associative memory.* Knoblauch surveys the current state-of-art in the paper "Neural Associative Memory for Brain Modeling and Information Retrieval". Starting with an exposure on traditional associative neural networks in the form of the classical Willshaw model, solutions using spiking neurons are suggested, and it is discussed whether distributed neural associative memories have practical advantages over localized storage.

Many applications use traditional neural networks as function approximators when the function needed is unknown. Given a set of datapoints, neural networks have proven to be very successful at interpolating datapoint in between, thus approximating the function.

As Ianella & Kindermann point out in their article "Finding Iterative Roots with a Spiking Neural Network", a more complex but often also more rewarding task is to find the (recursive) components that make up the functions being approximated. In their paper, they demonstrate progress towards learning such *iterative roots* in a spiking neural network. Two algorithms for learning are presented, one semi-supervised where the function is known and the task is to find the roots of the function, the other without this extra knowledge.

One important issue with the application of spiking neural networks is the fact that they are typically computationally more intensive than traditional neural networks. It has already been established that the event based nature of timed spikes drastically reduces the communication load between neurons, allowing in principle for efficient parallel implementations.

That still leaves open how to efficiently compute at what time a neuron fires given its input spikes. In "Spiking Neural Nets with Symbolic Internal State", O'Dwyer & Richardson present an algorithm to efficiently compute this firing based on symbolic manipulation and interval arithmetic.

We believe these papers show that substantial progress is being made towards the application of spiking neural networks: the work by Verstraeten et al. shows that spiking neural networks may have real promise in speech recognition; Booij & Nguyen derive more effective learning rules; Knoblauch treats the capacities and also limitations of spiking neural networks for associative memory; Ianella & Kindermann present work aimed at finding functional roots, and O'Dwyer & Richardson present an algorithm that helps to efficiently compute the ongoing activity in a spiking neural network.

In addition to this already very "hands-on" progress towards practical spiking neural networks, it is worth remarking that work has been presented recently that makes spiking neural networks even more interesting from a practical point of view: papers by Deneve [2], Rao [4] and Zemel et al [5] propose different ways of performing Bayesian inference in spiking neural networks. These works show real promise, and could be the basis for many applications. Surely the applications of spiking neural networks presented in this special issue will only be the start of many more to come.

References

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