Polychrony detection in raster plots

This manuscript ([permalink]) was automatically generated from [SpikeAI/polychronies@fdfe597] on December 6, 2021.

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Abstract

A crucial advantage of Spiking Neural Networks (SNNs) architectures lies in its processing of temporal information. Yet, most SNNs encode the temporal signal as an analog signal and try to “cross-compile” classical Neural Network to a spiking architecture. To go beyond the state-of-the-art, we will review here on one core computation of a spiking neuron, that is, is its ability to switch from the classical integrator mode (summing analog currents on its synapses) to a synchrony detector where it emits a spike whenever presynaptic spiking inputs are synchronized. To overcome the diversity of input presynaptic patterns, we will explore different existing architectures to learn to detect stable “polychronous“ events, that is, volleys of spikes which are stable up to certain synaptic delays. These models will be compared in light of neuroscientific and computational perspectives.

introduction

Most importantly, it will provide with a detection ability requiring only a few spikes, and therefore in line with the performance observed in biological systems, like the ability for humans to detect the presence of an animal in an image in a few milliseconds (Thorpe et al (1996). Speed of processing in the human visual system. Nature, 381(6582), 520-522). Such biological observations would serve as benchmarks to compare our proposed architecture to conventional solutions. (1] S Thorpe, D Fize, and C Marlot, Nature 381.6582 (1996), pp.520-522.

The approach which is currently most prominent in the Spiking Neural Networks community is to use existing algorithms from machine learning and to adapt them to the specificity of spiking architectures. One such example is to adapt the successes of deep learning algorithms and to transfer the back-propagation algorithm to SNNs, for instance with a surrogate gradient. This approach is quite successful, and SNNs approach in some case the performance of Deep Learning algorithms, for instance on the N-MNIST dataset for categorizing digits in a stream of events. However, most biological neural systems use spikes and are obviously more efficient than current state-of-the-art vision systems, both in terms of efficiency (accuracy), in speed (latency), and energy consumption. There is therefore an immense gap in the way we understand biology to translate it to the efficiency of SNNs. Our approach will be to focus on the temporal representation of information directly. In particular, our objective is to fully exploit the capacity of spiking neurons to detect synchronous patterns.

While my previous expertise was based on the modeling of how SNNs process information (Perrinet, Samuelides and Thorpe, 2004) and how these networks may be tuned in a unsupervised manner to their input (Perrinet, Samuelides and Thorpe, 2003), many different SNN architectures may provide robust solutions. Since that time, I have worked on exploring the space of all solutions which are the most efficient to solve a given problem using Bayesian methods. This culminated in defining a hierarchical model performing predictive coding (Boutin et al, 2020). However, this network is analog and simulations perform too slowly, even on advanced GPU architectures, to be used for real life situation. We have recently developed a similar architecture but based on a SNN architecture. In particular, this model is event-based from one end (sensory input from event-based cameras) to the other (classification) and its intermediate layers are learned in a self-supervised fashion (Grimaldi et al, 2021: a, b).

timing encodes profile

Our approach would be distinct than these approaches from us and colleagues as we will directly deal with delays in the system at the presynaptic level. I have an extensive expertise in the domain of temporal delays in the nervous system, both at the neural (Perrinet, Adams, Friston, 2012) and behavioral (Khoei et al, 2017) levels. Extending this knowledge to the optimization of delays in a SNN will provide a breakthrough in the efficiency of these networks. Our expertise in reproducing the HOTS network (Grimaldi et al, 2021: a, b) will be crucial in the swift realization of this project.

Celebrini

[4] T Gollisch and M Meister, Science 319.5866 (2008), pp. 1108-1111.

book gradually leads the reader from the macroscopic cortical anatomy and standard electrophysiological properties of single neurons to neural network models and synfire chains

sparse in time and space [2] AL Barth and JF Poulet Trends in Neurosciences 35.6 (2012), pp. 345-355. [3] CC Petersen and S Crochet, Neuron 78.1 (2013), pp. 28-48.

cortical songs

Ikegaya Y, Aaron G, Cossart R, Aronov D, Lampl I, Ferster D, Yuste R. 2004. Synfire chains and cortical songs: temporal modules of cortical activity. Science (New York, NY) 304:559–564. (Ikegaya et al., 2004)

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polychronization

Rapid Formation of Robust Auditory Memories: Insights from Noise (Agus et al., 2010)

Detecting patterns in raster plots

spike pattern clustering

Paper by (Grossberger et al., 2018)

- Temporally ordered multi-neuron patterns likely encode information in the brain. We introduce an unsupervised method, SPOTDisClust (Spike Pattern Optimal Transport Dissimilarity Clustering), for their detection from high-dimensional neural ensembles. SPOTDisClust measures similarity between two ensemble spike patterns by determining the minimum transport cost of transforming their corresponding normalized cross-correlation matrices into each other (SPOTDis).
- Detecting these temporal patterns represents a major methodological challenge.
- Many approaches to this problem are supervised, that is, they take patterns occurring concurrently with a known event, such as the delivery of a stimulus for sensory neurons or the traversal of a running track for hippocampal place fields, as a “template” and then search for repetitions of the same template in spiking activity :
- Nadasdy Z, Hirase H, Czurko A, Csicsvari J, Buzsaki G. Replay and time compression of recurring spike sequences in the hippocampus. J Neurosci. 1999;19(21):9497–507. pmid:10531452
- Lee AK, Wilson MA. A combinatorial method for analyzing sequential firing patterns involving an arbitrary number of neurons based on relative time order. J Neurophysiol. 2004;92(4):2555–73. pmid:15212425
- Davidson TJ, Kloosterman F, Wilson MA. Hippocampal replay of extended experience. Neuron. 2009;63(4):497–507. pmid:19709631

- only one spike per neuron: fig 1A = "For each pattern and each neuron, a random position was chosen for the activation pulse."
- t-SNE projection with HDBSCAN labels shows that our clustering method can retrieve all patterns from the data.
- data available @ https://doi.org/10.1371/journal.pcbi.1006283.s013

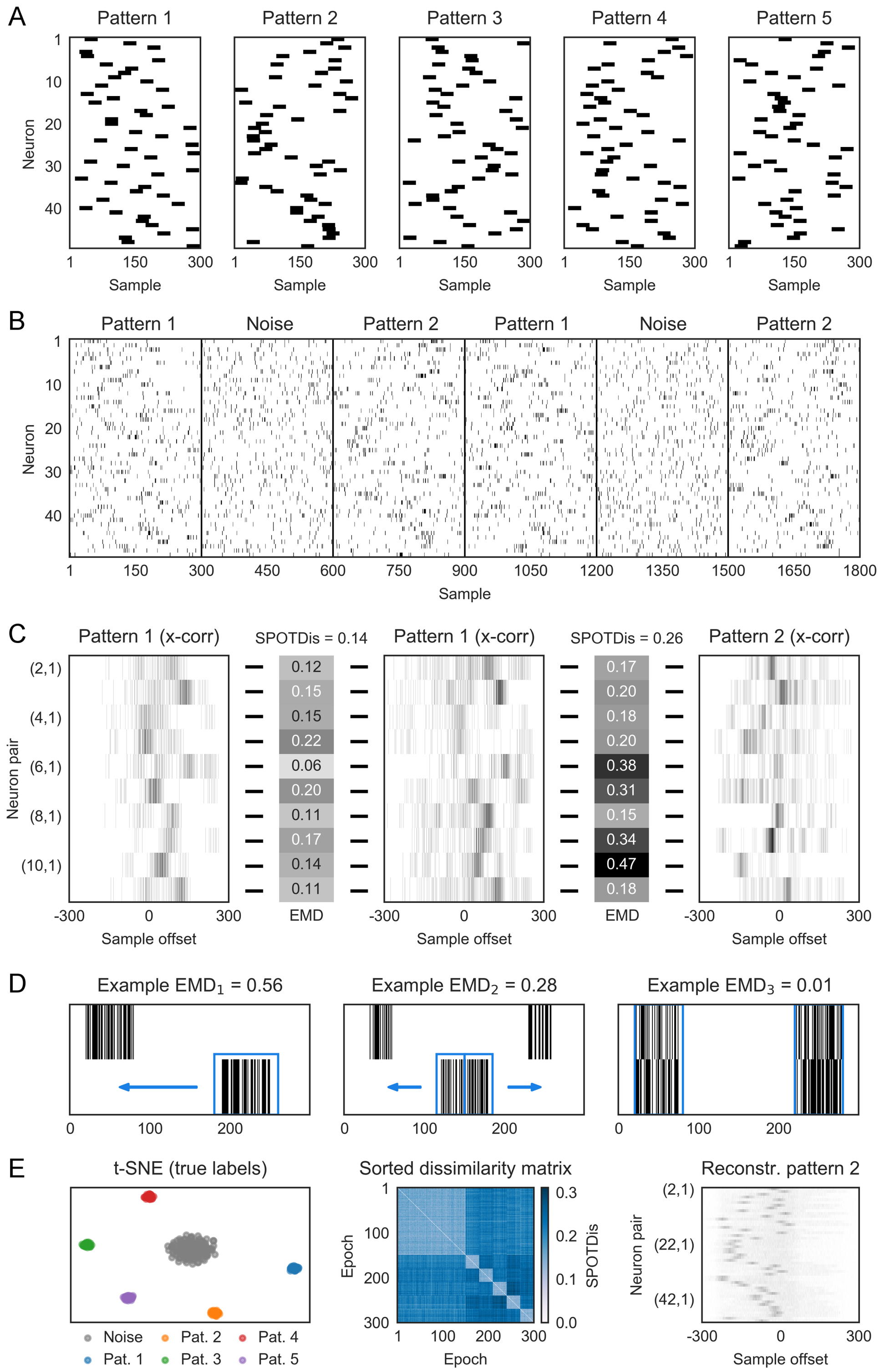

Figure 1: Fig 1 of (Grossberger et al., 2018): "Simulated example illustrating the steps in SPOTDisClust."

(Russo and Durstewitz, 2017)

- "Here we present such a unifying methodological and conceptual framework which detects assembly structure at many different time scales, levels of precision, and with arbitrary internal organization." by Russo and Durstewitz (2017)

- sliding windeow as in (**Grün2002?**)

Rastermap

- https://www.janelia.org/lab/stringer-lab ("GitHub - MouseLand/rastermap," n.d.)
- https://www.biorxiv.org/content/10.1101/374090v2 Stringer et al. (2019b)

Paper by (Moser and Natschlager, 2014)

On Stability of Distance Measures for Event Sequences Induced by Level-Crossing Sampling

outline

The rest of this review paper is organized as follows: * polychronization * We review theoretical foundations of spike time coding in a neuron: We will describe the Spike-Time Dependent Plasticity (STDP) rule which implement an unsupervised learning aiming at optimizing the detection of polychronous patterns, that is volleys of spikes which are synchronized, up to some stable pattern of pre-synaptic delays. This STDP rule will be based by the inversion of the generative model for spike formation and will therefore be derived by a Bayesian approach. This will decouple the active synapses (similarly to a logistic regression) from the values of possible synaptic delays. * Application to Image processing using sparse spiking representations: Using the core computational unit defined, extension of the computation to a topographic representation similar to that observed in the primary visual cortex of mammals. design of micro-circuits with specific lateral interactions will allow us to design efficient micro-circuits for the sparse representation of images. * Discussion on Ultra-fast vision: existing datasets recorded in natural settings or indoor scenes with event-based cameras.

Methods

Outline of the algorithm

Learning delays

STDP

(Perrinet and Samuelides, 2002) : coherence detection (Perrinet et al., 2001) : STDP

test notebook

```
import numpy as np
print(f'{np.pi=}')
```

```
np.pi=3.141592653589793
```

```
```

results on natural images

in (n.d.), we generate raster plots from natural images

A natural documentary, Planet Earth with David Attenborough

```
filename = './nat_inputs/PlanetEarth.mp4'  # filename of the movie
```

Results

References

n.d. https://laurentperrinet.github.io/sciblog/posts/2018-11-05-statistics-of-the-natural-input-to-a-ring-model.html

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