Review on Polychrony detection in biological and artificial raster plots

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Abstract

The response of a biological neuron depends largely on the precise timing of the sequence of presynaptic spikes as they reach the basal dendritic tree. This temporal aspect of the neuronal code is essential in understanding information processing and also applies to the output of an event-based camera. However, most neuronal models do not take advantage of this minute temporal dimension, especially in exploiting the variety of synaptic delays on the dendritic tree.

We will define the motifs of precise temporal patterns as polychronous groups following the model of Izhikevich (2006). This manuscript reviews current litterature on *polychrony detection* in raster plots. It is work in progress, where anybody interested can *openly* join.

We will first review some biological and theoretical evidence for polychrony in the neural information processing. We will then review some models for the detection of such polychronous groups in arbitrary raster plots, synthetic, biological or artificial (notably from event-based cameras). Then, we will try to outline some possible strategies for learning these patterns and finally discuss possible perspectives.

introduction: precise temporal patterns in the brain

ultra fast neural codes

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).

how timing encodes analogous profile

[1] T Gollisch and M Meister, Science 319.5866 (2008), pp. 1108-1111. Fig. 1. Ganglion cell responses to flashed gratings with different spatial phases. Fig. 4. Responses of a fast OFF ganglion cell to a flashed natural image. (For results from other cell types, see fig. S9.)

Celebrini [2]

timing in natural images

in [3], we generate raster plots from natural images

Note also that timing is not entirely sensorial or internal but in [4], they found that "timing accuracy was improved when the environment afforded cues that rats can incorporate into motor routines. Timing, at least in animals, may thus be fundamentally embodied and situated."

delays

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 [5] and behavioral [6] 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 [**doi:Grimaldi2022pami?**] will be crucial in the swift realization of this project.

synfire chains

In [8] corticonics: The 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.

M. Diesmann, M. O. Gewaltig, A. Aertsen, Nature402, 529 (1999).

- [9] : from synfire chains to Synfire braids

- recent theories of binding by synchrony : Fries 2005 trends cog neuro with spikes arriving at peak susceptibility (top of a cycle) or down, van Rullen, Laura Dugué

- A notable exception is the polychronization model of Izhikevich (2006), which combined the construction of a random recurrent model of spiking neurons including such delays and whose weights evolved with a Spike-Time Dependent Plasticity (STDP) learning rule. In this model, raster plot analysis showed repeated activation of Polychronous Groups (PGs), i.e., specific spike patterns with a specific sequence of activations.

precise temporal patterns TODO read [10]

[10] Luczak A, McNaughton BL, Harris KD. Packet-based communication in the cortex. Nat Rev Neurosci. 2015;16(12):745–55.

In [11], it was shown that attentional information from V4 or arousal can change the timings of groups of events in V1. They develop a HMM model for quantifying the transitions. "In this study, van Kempen et al. show that fluctuations in neural excitability are coordinated between visual areas with retinotopic precision. Top-down attention drives interareal coordination along the reverse cortical hierarchy, predicting better behavioral performance with increased coordination."

cortical songs [12]

- Ikegaya and colleagues worked on spontaneous activity in vitro and in vivo. They demonstated that in cortical activity, we can find a repetition of several motifs. In PSCs, but also in spike activity. These sequences repeat after minutes and have a precise spatio temporal structure with a ms precision. They can be specific of a particular layer or colomn, are synchronized with network activity oscillation and can involve several cells. They also demonstated that these sequences can form supersequences : the cortical songs. It consist of the assembly of several sequences which repeat in a specific order with a compressed timing.

- "We find precise repetitions of spontaneous patterns of synaptic inputs in neocortical neurons in vivo and in vitro. These patterns repeat after minutes, maintaining millisecond accuracy."

- Precisely repeating motifs of spontaneous synaptic activity in slices: duration around 1s +/- .5 s. Some events in motifs are of similar size but sometimes absent - better described by Bernouilli than SE (and covariance)

- *in vivo* spontaneous activity also reveals repeating sequences. About 3000 sequences, each involving 3-10 cells out of about 900, and last up to 3 seconds

- topography: "Sequences had specific topographic structures, in some cases involving only a particular layer or a vertical column of cells or cells located in a cluster (Fig. 4, A and B, and fig. S3B). (...) Therefore, repeating temporal patterns of activation (...) were associated with a structured spatial organization of the neurons that formed them."

- "Cortical songs: modular assemblies of repeated sequences": hierarchical detection.

- in cotical songs, there is a "compressing timing" which may be taken into account by a similar mechanism as maxpooling in CNNs for space, but in time. Or there may be a mechanism for controlling the replay speed (pulvinar, ... , ?)

A in vitro

i

a   b   c

ii

B in vitro

a   b   c

C in vivo

i

ii

200 ms

Fig. 1. from [12]   Repeated motifs of spontaneous synaptic activity in vitro and in vivo. (A) Repeated motifs of intracellular activity from layer 5 pyramidal neurons in slices. Panels show segments (red) of the same voltage-clamp recording from the same cell repeating seconds or minutes after the initial occurrence (blue). Arrows indicate timings of repeated PSCs. (i) Upper trace: low–temporal resolution display of spontaneous activity of a neuron. Lower traces: higher resolution display of the repeated motif at indicated regions of the trace (a to c). (ii) Example of a longer motif. (B) Three repetitions of a motif. The top traces show the motifs superimposed on each other (blue, green, and red), the middle traces show these same traces individually, and the bottom traces show temporally magnified regions of the motifs (a to c). (C) Repeated sequences of intracellular current-clamp recordings in vivo. Two (i) and three (ii) repetitions of motifs are shown. Shuffle tests were performed on traces (i), a to c, yielding significantly fewer repeats (fig. S2, P < 0.02). In (i), the blue trace is shifted –2.75 mV; in (ii), the blue trace is shifted –1.58 mV, and the green +0.79 mV.

It is interesting to make a parallel with the "Rapid Formation of Robust Auditory Memories" reported in [13] which uses noise patterns. They " used random waveforms to probe the formation of new memories for arbitrary complex sounds. A behavioral measure was designed, based on the detection of repetitions embedded in noises up to 4 s long." The task is to detect the repetition of the same (frozen) noise within a trial. " Unbeknownst to listeners, some noise samples reoccurred randomly throughout an experimental block." they showed that the "repeated exposure induced learning for otherwise totally unpredictable and meaningless sounds" by showing that the sensitivity increases in that case. Note that "acoustical analyses failed to reveal any obvious differences between good and bad noises" and that "Time reversal had no significant effect on the RefRN advantage" (quite surprising). The Learning is unsupervised (statistical, automatic), fast-acting (phase transition, "insight"), and long-lasting (memorization).

polychronization

outline

This section has provided evidence that polychronous groups are an important apsect of information representation in biology with important application in data analysis and neuromorphic engineering. The rest of this review paper is organized as follows.

First, we will review models for the detection of polychronous groups:

- 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. We review theoretical and computational foundations of PG detection in models.

- 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.

Finally we will discuss future avenues for effective PG detection and learning in event streams.

Models of polychronization detection in models

Izhikevitch

spike distances

Detecting patterns in biological raster plots

decoding neural activity

In generic linear non linear lnl models, the output is assumed to be poisson. As such a simple decoding strategy is to asscume it is to b inferned for a given tuning curves (Jayazeri) or simply by a simple regression [14]. This latter model assumes a Bernoulli model for the generation of spikes such that the decoding amounts to a single-layer logistic regression.

Rastermap : decoding large-scale data

- https://www.janelia.org/lab/stringer-lab
- described in [15]
- rastermap
- deconvolution strategy
- based on a linear model

Stringer et al 2019, Nature [16]

- "A neuronal population encodes information most efficiently when its stimulus responses are high-dimensional and uncorrelated, and most robustly when they are lower-dimensional and correlated. Here we analysed the dimensionality of the encoding of natural images by large populations of neurons in the visual cortex of awake mice."
- Data availability: All of the processed deconvolved calcium traces are available on figshare, together with the image stimuli.
- Code availability: The code is available on GitHub.

Stringer et al 2019, Science [17]

- Stringer et al. analyzed spontaneous neuronal firing, finding that neurons in the primary visual cortex encoded both visual information and motor activity related to facial movements. The variability of neuronal responses to visual stimuli in the primary visual area is mainly related to arousal and reflects the encoding of latent behavioral states.

- see also the work showing that you can encode very precise orientation information by using many neurons: [18]

detecting structured temporal patterns
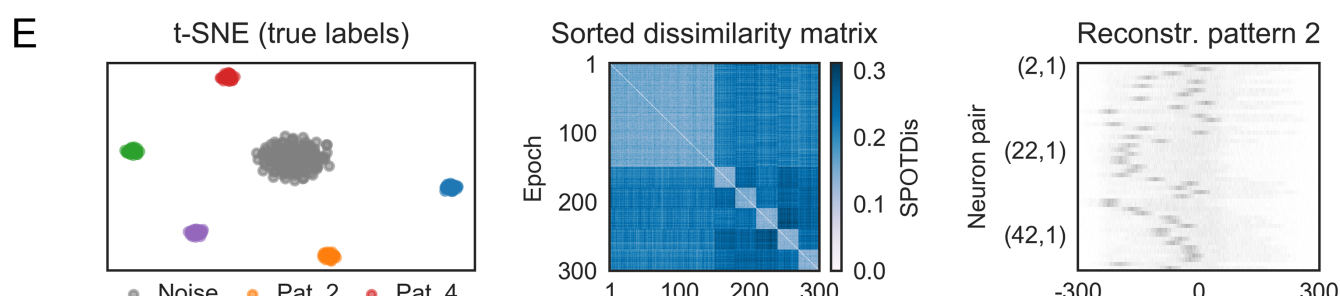
Paper by Grossberger, 2018 [19]

- 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
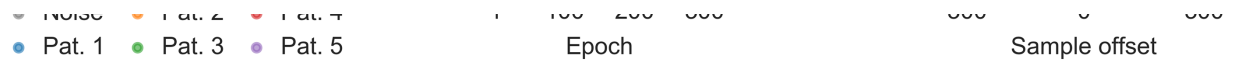
between two ensemble spike patterns by determining the minimum transport cost of transforming their corresponding normalized cross-correlation matrices into each other (SPOTDis).

- 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

A

Pattern 1 Pattern 2 Pattern 3 Pattern 4 Pattern 5

Neuron / Sample

B

Pattern 1   Noise   Pattern 2   Pattern 1   Noise   Pattern 2

Neuron / Sample

C

Pattern 1 (x-corr)   SPOTDis = 0.14   Pattern 1 (x-corr)   SPOTDis = 0.26   Pattern 2 (x-corr)

Neuron pair

(2,1)   0.12   0.17
        0.15   0.20
(4,1)   0.15   0.18
        0.22   0.20
(6,1)   0.06   0.38
        0.20   0.31
(8,1)   0.11   0.15
        0.17   0.34
(10,1) 0.14   0.47
        0.11   0.18

Sample offset   EMD   Sample offset   EMD   Sample offset

D

Example EMD$_1$ = 0.56   Example EMD$_2$ = 0.28   Example EMD$_3$ = 0.01

E

t-SNE (true labels)   Sorted dissimilarity matrix   Reconstr. pattern 2

Noise   Pat. 2   Pat. 4

Epoch / SPOTDis

Neuron pair
(2,1)
(22,1)
(42,1)
-300   0   300

Figure 1: Fig 1 of [19]: "Simulated example illustrating the steps in SPOTDisClust. A) Structure of five "ground-truth" patterns (…). For each pattern and each neuron, a random position was chosen for the activation pulse. B) Neuronal output is generated according to an inhomogeneous Poisson process, with rates dictated by the patterns in (A)." (© Authors under a CC licence)

- "However, SPOTDis has two principal weaknesses that we address here: (1) Its computational complexity, for comparing two time epochs, is O(N2), where N is the number of neurons. This becomes a major problem for computing an M◻M dissimilarity matrix (for M time epochs) for thousands of neurons. (2) It relies exclusively on pairwise spike-timing relationships (i.e 2nd order correlations), because it does not solve the optimal transport problem for the entire spike pattern, but only for neuron pairs separately. Hence, it may not be sensitive to higher-order correlations in spiking patterns. Here, we develop a novel dissimilarity measure for multi-neuron spiking patterns called SpikeShip, which has linear computational complexity of O(N). We achieve this by (1) computing the minimum transport cost of spikes for each spike train separately, and (2) discounting a global translation term in the transport flow across neurons."
  https://doi.org/10.1101/2020.06.03.131573;

Paper by Russo et al 2017 [20]

- "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 [20]
- sliding window as in [21] ("Numerous other statistical procedures for detecting assemblies or sequential patterns have been proposed previously") - extended to multiple lags [22]
- based on a "non-stationarity-corrected parametric test statistic for assessing the independence of pairs" and "an agglomerative, heuristic clustering algorithm for fusing significant pairs into higher-order assemblies"

Paper by [23]

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

Neural Variability and Sampling-Based Probabilistic Representations in the Visual Cortex [24]

- Stochastic sampling links perceptual uncertainty to neural response variability
- Model accounts for independent changes in strength and variability of responses
- Model predicts relationship between noise, signal, and spontaneous correlations
- Stimulus statistics dependence of response statistics is explained

Learning to detect polychronous groups

Learning weights … and delays

spike time coding in a neuron: We will describe the Spike-Time Dependent Plasticity (STDP) [25] 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.

[26] : coherence detection [27] : STDP

[28]

Bio-plausible Unsupervised Delay Learning for Extracting Temporal Features in Spiking Neural Networks Alireza Nadafian, Mohammad Ganjtabesh

The plasticity of the conduction delay between neurons plays a fundamental role in learning. However, the exact underlying mechanisms in the brain for this modulation is still an open problem. Understanding the precise adjustment of synaptic delays could help us in developing effective brain-inspired computational models in providing aligned insights with the experimental evidence. In this paper, we propose an unsupervised biologically plausible learning rule for adjusting the synaptic delays in spiking neural networks. Then, we provided some mathematical proofs to show that our learning rule gives a neuron the ability to learn repeating spatio-temporal patterns. Furthermore, the experimental results of applying an STDP-based spiking neural network equipped with our proposed delay learning rule on Random Dot Kinematogram indicate the efficacy of the proposed delay learning rule in extracting temporal features.

Learning sequences

- in [13], there are "good" and "bad" noises show that some patterns are more easy to disentangle - similar to bird songs and ecological niche.

- In Bellec [29], authors fit summary statistics of neural data with a differentiable spiking network simulator.

  - the loss function is the cross entropy (following Bernouilli hypothesis with a GLM where each unit is modelled with a SRM neuron [30] with recurrent dynamics)
  - sample and measure method to include latent / hidden neurons
  - comes with code https://github.com/EPFL-LCN/pub-bellec-wang-2021-sample-and-measure
  - V1-dataset : The dataset we used was collected by Smith and Kohn [49] and is publicly available at: http://crcns.org/data-sets/vc/pvc-11 - it is in a sense supervised with the input being the movie and the output the spikes recorded.

TODO: more bib to read

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learning pattern detection on natural images / event-based cameras

sparse coding on spatio-temporal data

HOTS

Grimaldi CBMI / PAMI

Discussion

dynamical models

Dumas and colleagues [31] : three levels / fourth paradigm [32] i.e., data exploration in which the scientific models are fit to the data by learning algorithms.

our model

Here, we develop a model for the efficient detection of such PGs based on the inversion of a probabilistic model defining the generation of the raster plot as a combination of such groups. We show that such an inference can be achieved by a neural-like computation that could itself be used as a spiking neuron, as can be implemented in a neuromorphic chip for instance. A first result is to show the efficiency of such a scheme in detecting different PGs occurring at specific times in synthetic data. The representational capacity of the PGs is particularly interesting compared to traditional models of neuronal encoding using spiking frequency. Our second result is to propose a novel learning method for learning PGs in raster plots in a self-supervised manner. Finally we demonstrate the use of this algorithm to the output of an event-based camera and how this may separate independent components from the stream of events. This end-to-end event-based computational brick could help improve the performance of current Spiking Neural Network solution currently used in neuromorphic chips.

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