Learning hetero-synaptic delays of spiking neurons for motion detection

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Abstract

The response of a biological neuron depends on the precise timing of afferent spikes. This temporal aspect of the neural code is essential in understanding information processing in neurobiology and applies particularly well to the output of neuromorphic hardware such as event-based cameras. However, most artificial neural models do not take advantage of this minute temporal dimension. Inspired by this neuroscientific observation, we develop a model for the efficient detection of temporal spiking motifs based on a layer of neurons with hetero-synaptic delays. Indeed, the connectivity of the dendritic tree allows to discriminate between different temporal sequences, and we show that this can be formalized as a time-invariant logistic regression which can be trained using labelled data. We apply this model to solve one specific computer vision problem, motion detection, and demonstrate its application to synthetic naturalistic videos transformed into event streams similar to the output of event-based cameras. In particular, we quantify how its accuracy can vary with the total computational load. This end-to-end event-driven computational brick could help improve the performance of future spiking neural network (SNN) algorithms currently used in neuromorphic chips.

Hetero-synaptic delays model

Illustration

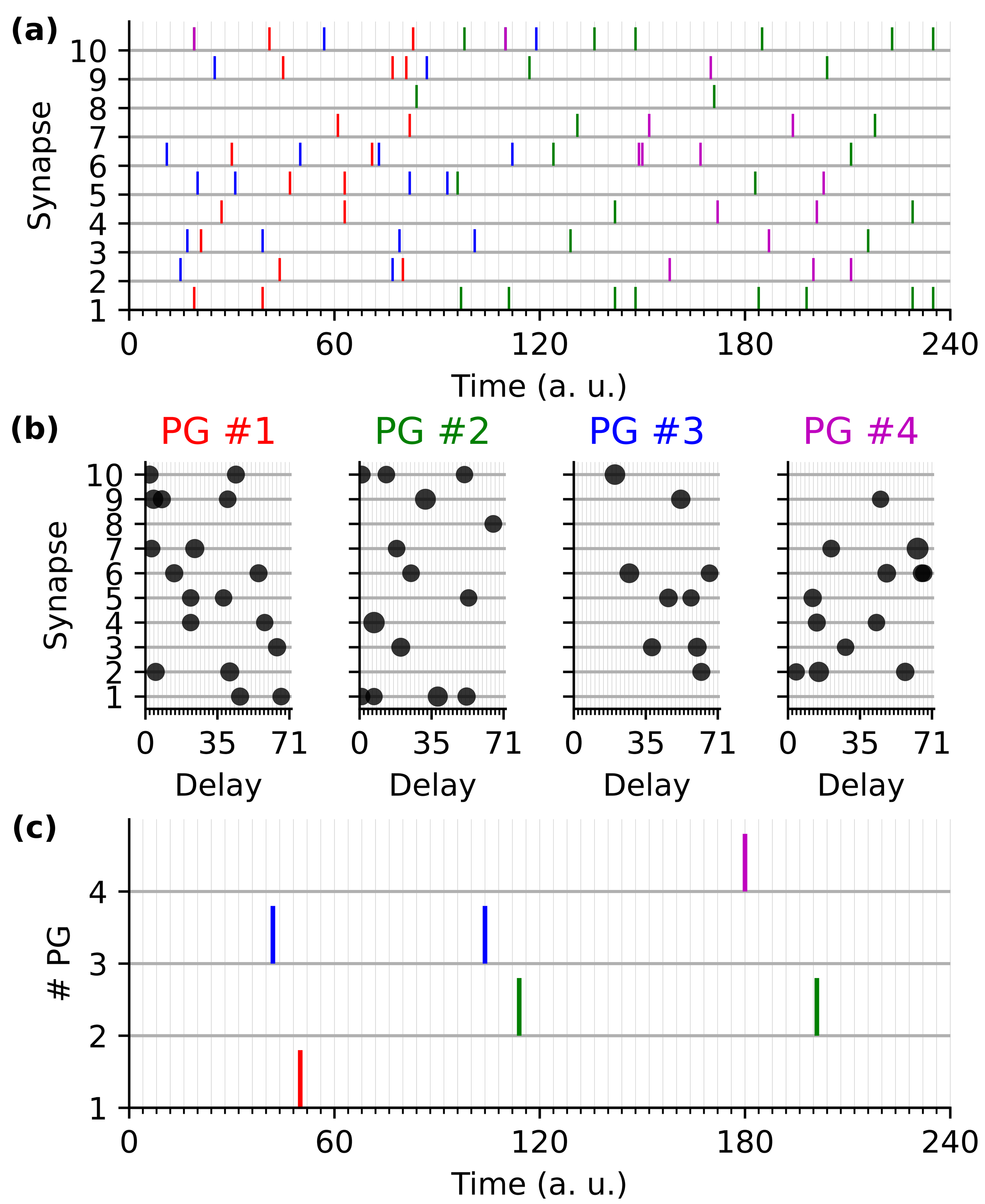

Figure 1: **(a)** The afferent information consists of the repeated occurrence of groups of precise motifs of spikes that we call "polychronous groups" (PGs). We highlight them by different colors, an information hidden to a detection model. **(b)** The model is defined as an assembly of neurons (here for 4 PGs) each defined by a set of different synapses described by weights (increasing with the radius of the black dots) at each different delay. The propagation of the afferent information through these delay may generate at each time step a synchronous pattern on a subset of synapses. **(c)** The output of the model provides with the predicted probability of occurrence of each PG pattern at any time, which may be used to generate a spike as a Bernoulli trial, providing in this particular case with an exact identification of PGs occurrences.

Mathematical formalism

Event stream:

$$\boxed{\epsilon = \{(a_r, t_r)\}_{r\in[1,N_{ev}]}}$$

where $N_{ev} \in \mathbb{N}$ is the total number of events, t_r is the time occurence of event number r and a_r an associated address , which is typically in the form $a_r = (x_r, y_r, p_r)$.

Spiking neuron with hetero-synaptic delays:

$$\boxed{\sigma^n = \{(a_s^n, w_s^n, \delta_s^n)\}_{s\in[1,N_s^n]}}$$

is a set of N_s^n synapses, associated to neuron n, where each synapse σ_s^n is associated to a weight w_s^n, a delay δ_s^n and a presynaptic address a_s^n.

Active weights:

$$\boxed{\mathcal{W}^n(t) = \{w_s^n | a_r = a_s^n \text{ and } t = t_r + \delta_s^n\}_{r\in[1,N_{ev}],\, s\in[1,N_s^n]}}$$

Activation function (Multinomial Logistic Regression):

$$\boxed{Pr(k = n \mid t) = \frac{1}{Z}\text{exp}(\mathcal{C}^n(t) + b^n)}$$

where $\mathcal{C}^n(t) = \sum \mathcal{W}^n(t)$ is the sum of the synaptic weights and b^n is the bias linked to neuron n and $Z = \sum_{c=1}^{N_\text{class}} Pr(k = c \mid t)$.

Temporal convolution:
In this simplified model, we will consider that hetero-synaptic delays are limited in range such that the synaptic set can be represented by the dense matrix K^n giving for each neuron n the weights as a function of presynaptic address and delay: $\forall s \in [1, N_s^n], K^n(a_s^n, \delta_s^n) = w_s^n$ (see Figure 3). Using this dense representation, the counting $\mathcal{C}^n(t)$ defined above can be computed as a temporal convolution of the dense representation of the event stream E with the dense kernels formed by the set of synapses:

$$\boxed{\mathcal{C}^n = K^n * E}$$

Event-based Motion Clouds

To test our model, we will quantify its ability to categorize different motions. In that order, we will first define a set of synthetic stimuli, *Motion Clouds* [1], which are natural-like random textures for which we can control for velocity, among other parameters.

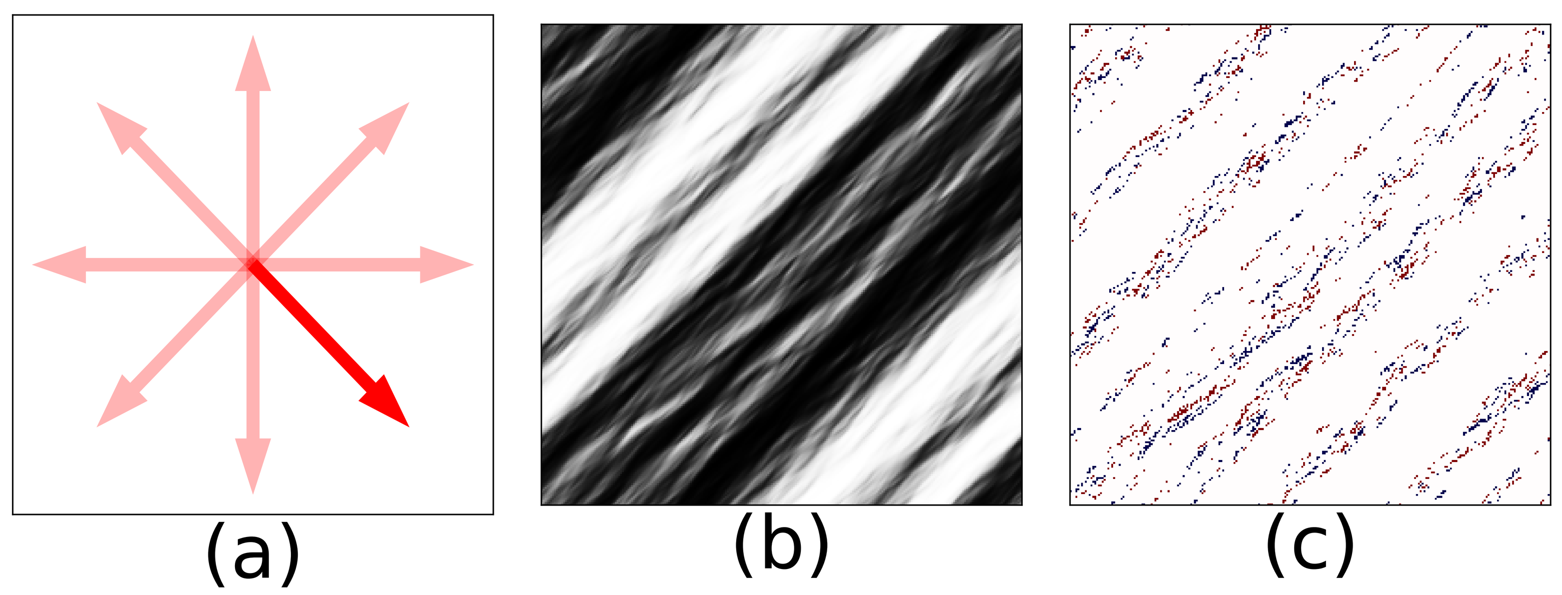

Figure 2: **Motion detection task.** *(a)* The motion direction represented as the plain red vector, other possible motion directions are represented in light red. *(b)* A screenshot of one generated naturalistic textured stimulus at a specific time. *(c)* The corresponding ON (in red) and OFF (in blue) event stream generated from the stimuli on (b) and constituting the input to the spiking neural network.

References

[1] P. S. Leon et al. "Motion Clouds: Model-based stimulus synthesis of natural-like random textures for the study of motion perception". In: *Journal of Neurophysiology* 107.11 (2012), pp. 3217–3226.

[2] X. Lagorce et al. "HOTS: A Hierarchy of Event-Based Time-Surfaces for Pattern Recognition". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence* 39.7 (2017), pp. 1346–1359.

Results

Learning hetero-synaptic delays

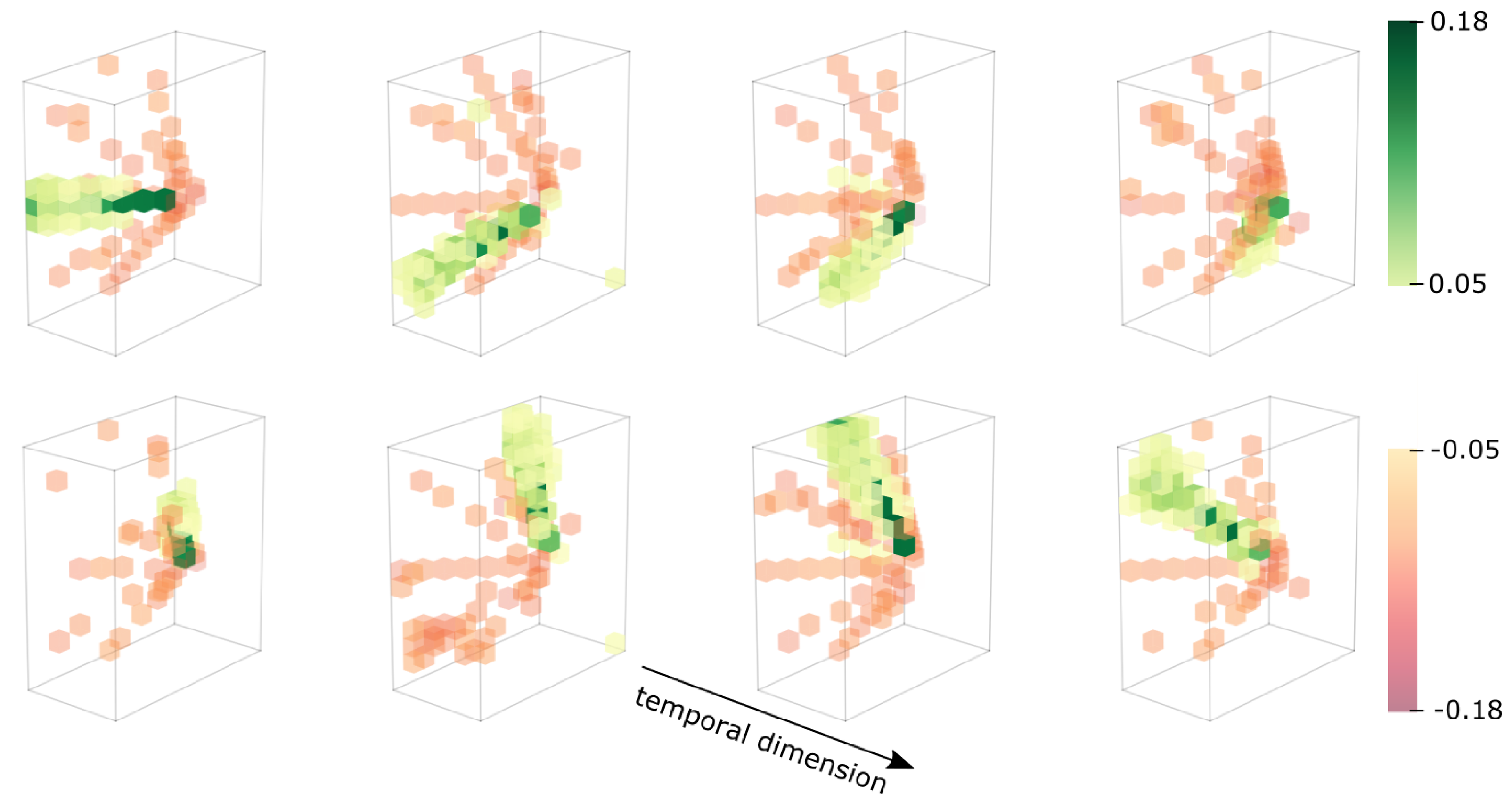

Figure 3: Representation of the weights for the 8 learned kernels of the model corresponding to the OFF polarities and selective to the different motion directions (because of the symmetry observed between the ON and OFF event streams, kernels are similar for the ON polarities). One sees positive (excitatory) coefficients for the specific direction of motion and negative (inhibitory) coefficients for all other directions.

Accuracy as a function of the number of computations

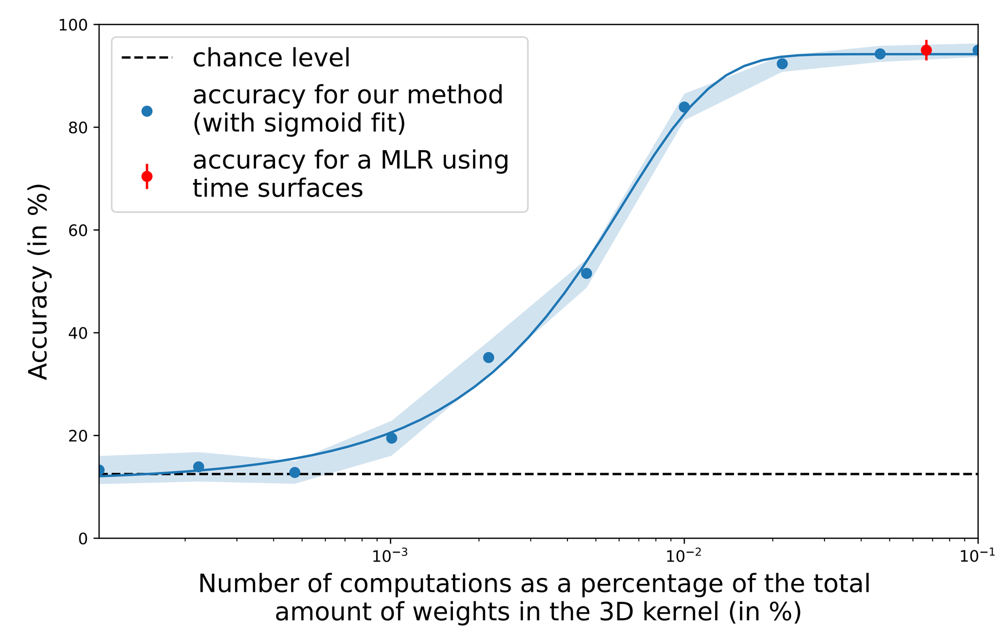

Figure 4: Accuracy as a function of the number of computation load for the hetero-synaptic delays model (in blue) and for a method using 2D time surfaces (in red) [2]. The relative computational load (on a log axis) is controlled by changing the percentage of active weights relative to the dense convolution kernel. We observe a similar accuracy than HOTS, yet that our model could achieve a similar accuracy with significantly less coefficients.

Conclusion

We have introduced a generic SNN using hetero-synaptic delays and shown how it compares favorably with a state-of-the-art event-based algorithm used for classification [2]. This shows that we may use the precise timing of a spike to enhance neural computations. One advantage of our model is the generality of the approach. Indeed, this supervised learning scheme can be extended to a novel task by defining a new set of supervision pairs (for instance supervised by local orientation) which would lead to the emergence of new kernels adapted to this new task. This constitutes a major advantage over other algorithms which derive event-based algorithms from specific physical rules. We aim at extending the application of this model on more generic datasets acquired in natural conditions for progressively more complex tasks such as time-to-contact maps.

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