Detection of precise spiking motifs using spike-time dependent weight and delay plasticity

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Abstract

The spiking response of a biological neuron depends on the precise timing of afferent spikes. This temporal aspect of the neuronal code is essential in understanding information processing in neurobiology. In this model, raster plot analysis showed repeated activation of specific spiking motifs, which exhibit a precise temporal sequence of neural activations. Our first contribution is to develop a model for the efficient detection of temporal spiking motifs based on a layer of neurons with hetero-synaptic delays. Indeed, the variety of synaptic delays on the dendritic tree allows synchronizing synaptic inputs as they reach the basal dendritic tree. Second, we propose a bio-plausible unsupervised learning rule on both weights and delays through the derivation of a loss function which depends on the membrane potential of the spiking neuron and a sparseness regularization. We demonstrate on synthetic data that such a layer of spiking neurons is able to learn different repeating spatio-temporal motifs embedded in the spike train. Then, we test the robustness of the detection accuracy of the model by adding Poisson noise and compare it to a layer of Leaky-Integrate and Fire neurons trained with STDP. Results show a large improvement in performances when adding temporal delays for computations and a great increase in robustness to noise. We show that using synaptic delays for neuronal computations highly increases the representational capacities of a single neuron and its resilience to noise.

Hetero-synaptic delays model

Illustration

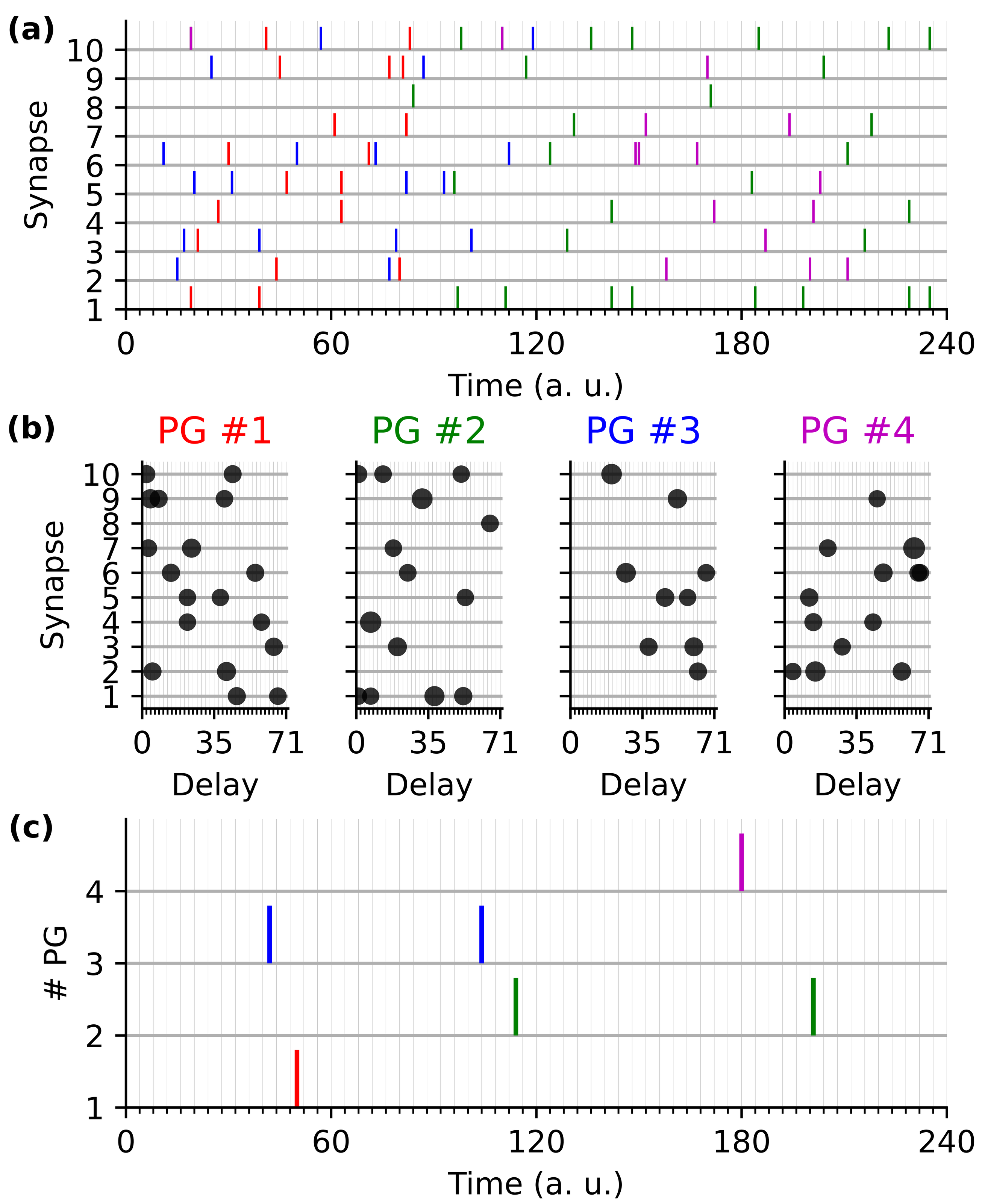

Figure 1: **(a)** The afferent information consists of the repeated occurrence of groups of precise motifs of spikes that we call "polychronous groups" (PGs). We highlight them by different colors, an information hidden to a detection model. **(b)** The model is defined as an assembly of neurons (here 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

Membrane potential of our spiking neuron model:

$$\boxed{V(t) = V_{rest} + \gamma \cdot (V_\theta - V_{rest}) \cdot \sum_s w_s \sum_{r \in \xi_s} K_s(t, t_r) - \sum_{f \in \xi_{\mathbf{p}}} (V_\theta - V_{rest}) \cdot H(t - t_f)}$$

where V_{rest} is the resting membrane potential, w_s is the synaptic weight of synapse s, ξ_s and $\xi_{\mathbf{p}}$ are both event streams associated respectively to the presynaptic address s and the postsynaptic address $\mathbf{p}$, V_θ is the membrane potential threshold and H is the Heaviside step function. K_s is the kernel applied to the input spikes.

Loss function:

$$\boxed{\mathcal{L}(t_f) = -V(t_f) + \lambda \cdot \left| N_f - r_{\mathbf{p}} \cdot T \right|}$$

λ is a regularization factor, N_f is the number of spikes that occured during time window T and $r_{\mathbf{p}}$ is the wished average firing rate for neuron $\mathbf{p}$.

Learning rule for the delays:

$$\boxed{\delta_s = \delta_s + \mu_\delta \cdot w_s \cdot \sum_{r \in \xi_s} \frac{\partial K_s(t_f,t_r)}{\partial \delta_s}}$$

Learning rule for the weights:

$$\boxed{w_s = w_s + \mu_w \cdot \sum_{r \in \xi_s} K_s(t_f, t_r)}$$

Homeostatic adaptation of the gain:

$$\boxed{\gamma = \gamma + \mu_\gamma \cdot \lambda \cdot N_f \cdot sgn(1 - \gamma)/T}$$

The non causal LIF kernel

$$K_s(t_f, t_r) = e^{-\frac{\left| t_f - t_r - \delta_s \right|}{\tau}}$$

$$\boxed{\frac{\partial V(t_f)}{\partial \delta_s} = \frac{w_s}{\tau} \sum_{r \in \xi_s} sgn(t_f - t_r - \delta_s) \cdot K_s(t_f, t_r)}$$

Conclusion

We have introduced an unsupervised learning rule (STDP) to adjust the synaptic delays in order to synchronize spikes from a repeating input pattern. This synchronization maximizes the membrane potential of the spiking neuron and allows the detection of a specific spatio-temporal motif embedded in the raster plot.

This rule can be combined with an STDP on the synaptic weights to allow more flexibility on the spatio-temporal motif to be learnt.

While the learning has been tested on different synthetic input patterns, a remaining goal is to train a layer of such spiking neurons to learn multiple patterns at the same time.

We aim at extending this unsupervised learning to realistic data: Dynamic Vision Sensor [1] signal, electro-physiological data, VSDI recordings, ...

References

[1] C. Posch et al. "Retinomorphic event-based vision sensors: bioinspired cameras with spiking output". In: *Proceedings of the IEEE* 102.10 (2014), pp. 1470–1484.

Acknowledgments

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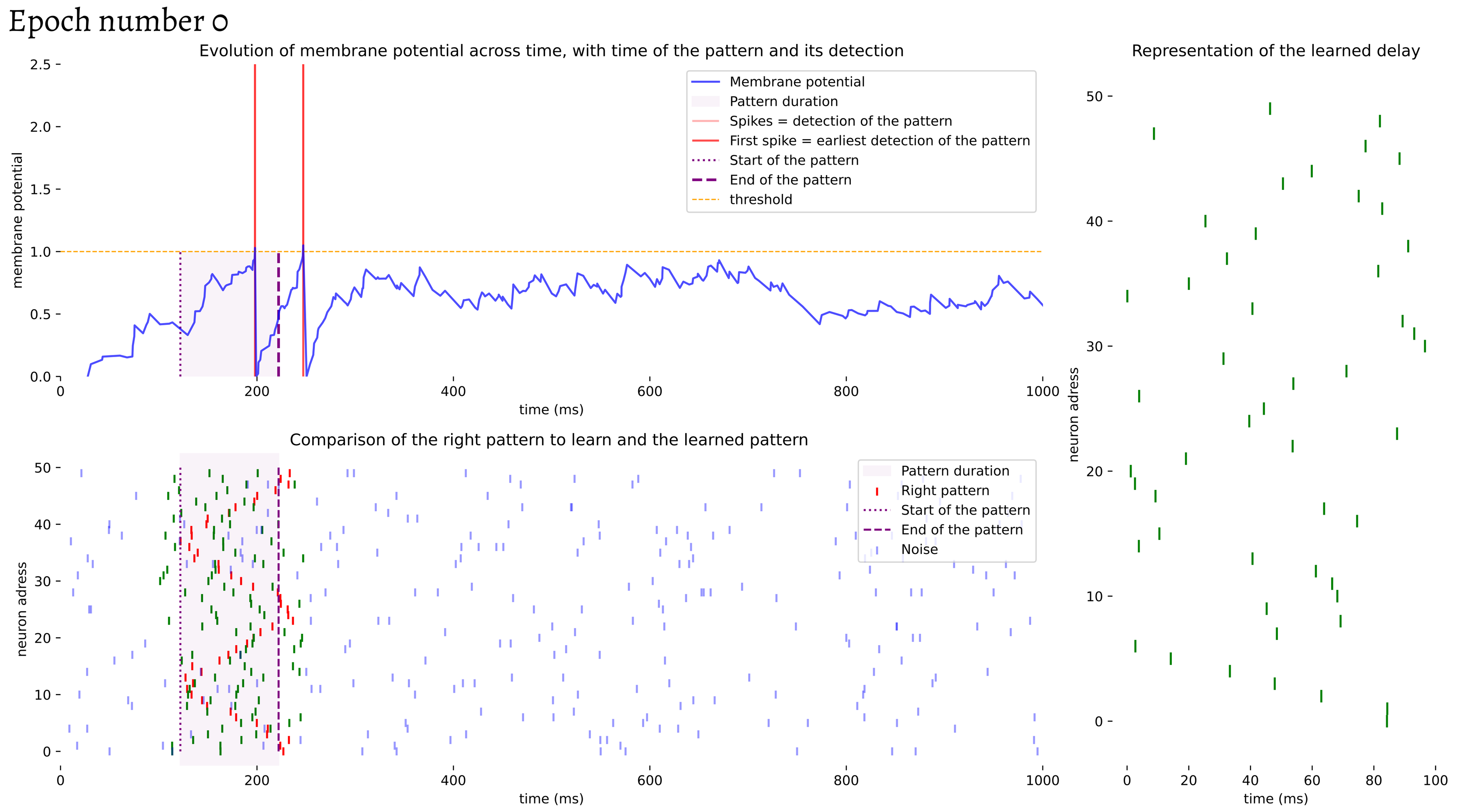
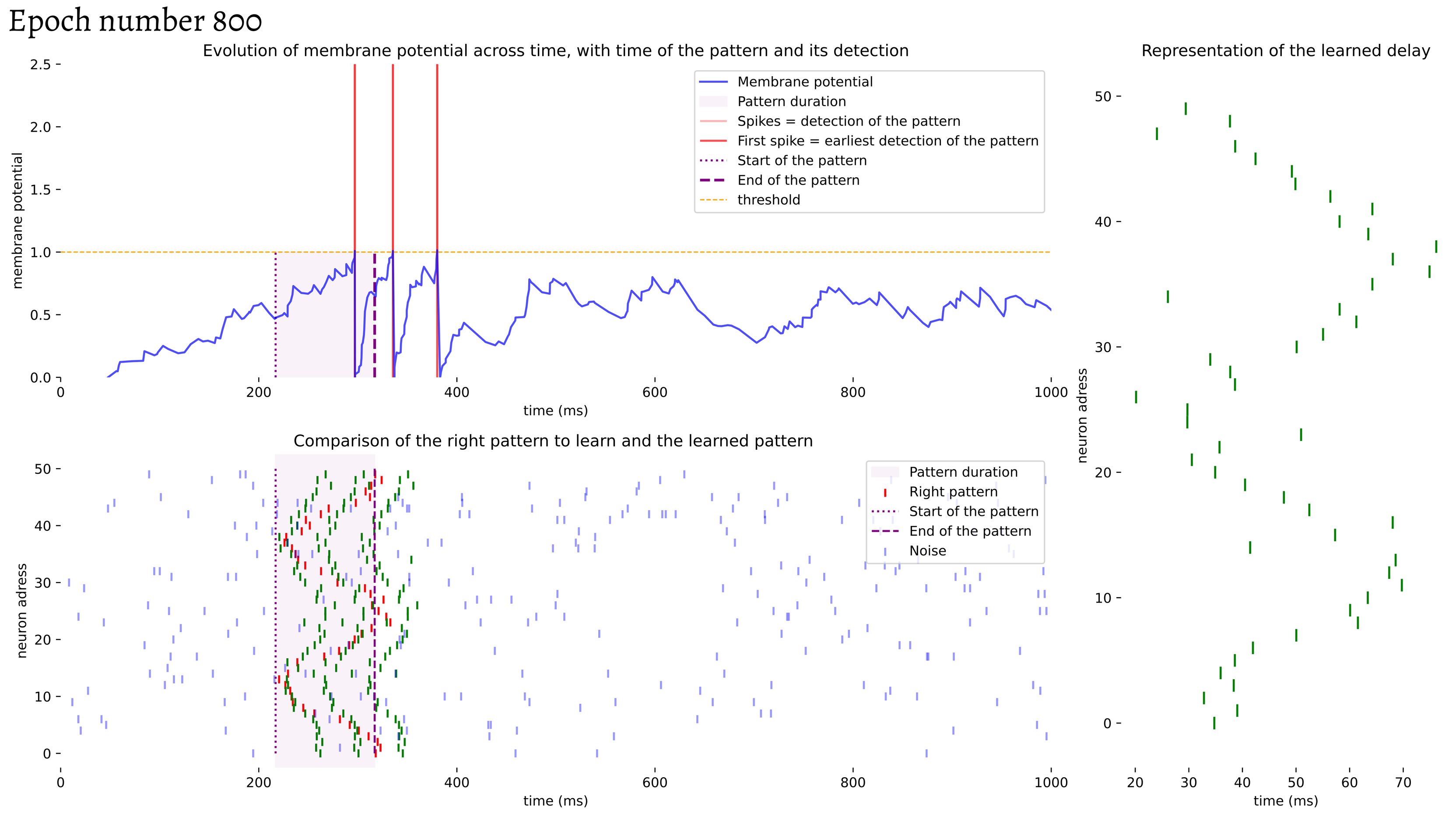
Results

Unsupervised learning of the synaptic delays

Epoch number 0



Epoch number 800



Epoch number 3200