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Modeling the development of optic flow processing in primates using spiking neural networks and Hebbian learning

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INTRODUCTION

During locomotion, retinal optic flow patterns are used by numerous animal species to monitor their heading and moving speed. In primates, optic flow is processed at the cortical level through a hierarchical network that first extracts local motion components and subsequently combines them to estimate egomotion properties. Although several computational models have been proposed to explain the underlying neural mechanisms (see e.g., Beyeler et al., 2016), their emergence during development in primate evolution still remains unclear. Here, we address this important issue using a spiking neural network (SNN) model, which was trained from both simulated data, and data collected under naturalistic navigation conditions. This SNN is endowed with synapses that learn using an unsupervised Hebbian rule - Spike-Timing-Dependent Plasticity (STDP).

METHODS

Datasets:

① 1200 synthetic sequences generated from the three components (translational, radial and rotational) of optic flow. Eight different conditions were used: leftward, rightward, downward, upward, forward and backward motions, clockwise and counterclockwise rotations derived from stimuli found in (Bichler et al., 2012). We used 3 different speeds (120, 240 and 480 pixels/s) and four different signal-to-noise ratios (SNR, 10, 3, 0, and -3 dB). These data were subsequently processed using ON and OFF spatio-temporal filters, thresholded and converted into spikes.

② Visual data captured by an event-based camera mounted on the head of a pedestrian walking within an urban environment (Mueggler et al., 2017).

Architecture of the SNN:

Our network was composed of two layers of leaky-integrate-and-fire (LIF) neurons. The first layer was retinotopically organized and its neurons only received spikes generated from a sub-portion of the visual field to ensure a local selectivity of motion. Neurons in the second layer were fully connected to the outputs of the first layer for a global perception of movement, as shown in figure 1.

Learning:

Unsupervised learning within the network was performed using an additive version of the STDP. The two layers were trained independently. Synaptic weights were normally distributed between 0 and 1. During learning, we used a 'winner-take-all' mechanism to prevent neurons from learning identical patterns (Chauhan et al., 2018).

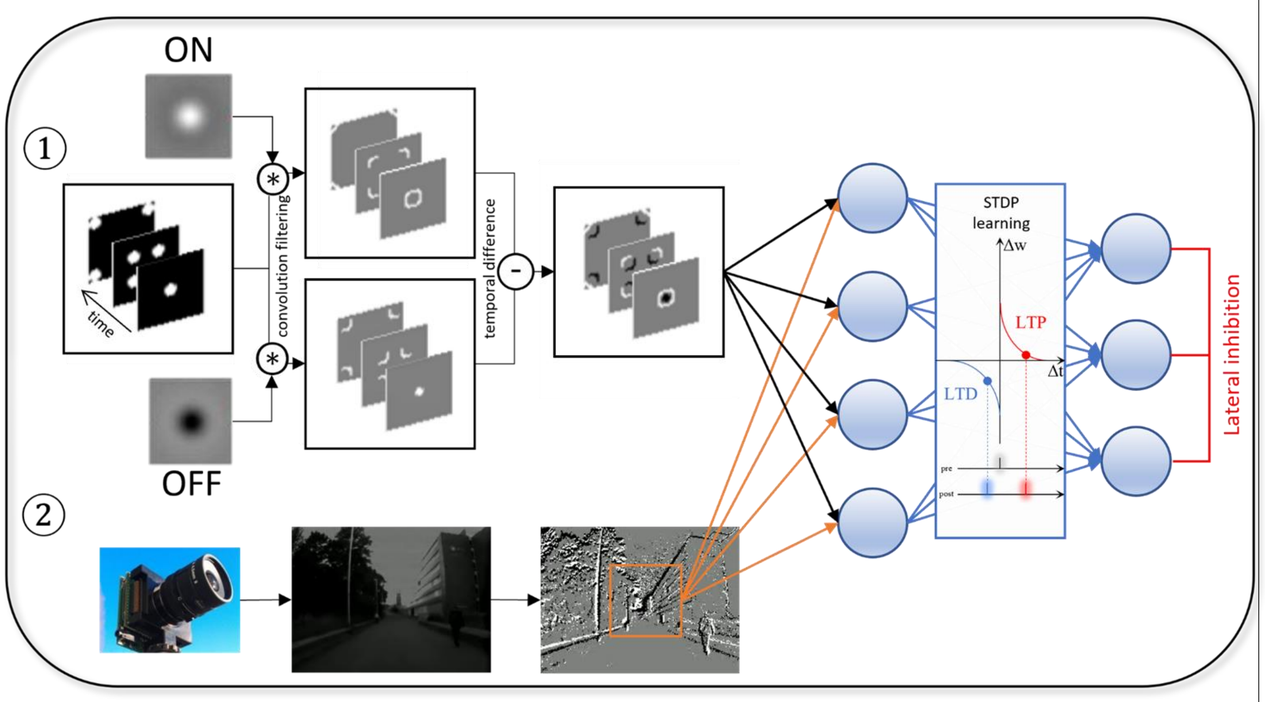

Figure 1: *Global overview of the network with the 2 different datasets and the STDP learning rule.*

RESULTS

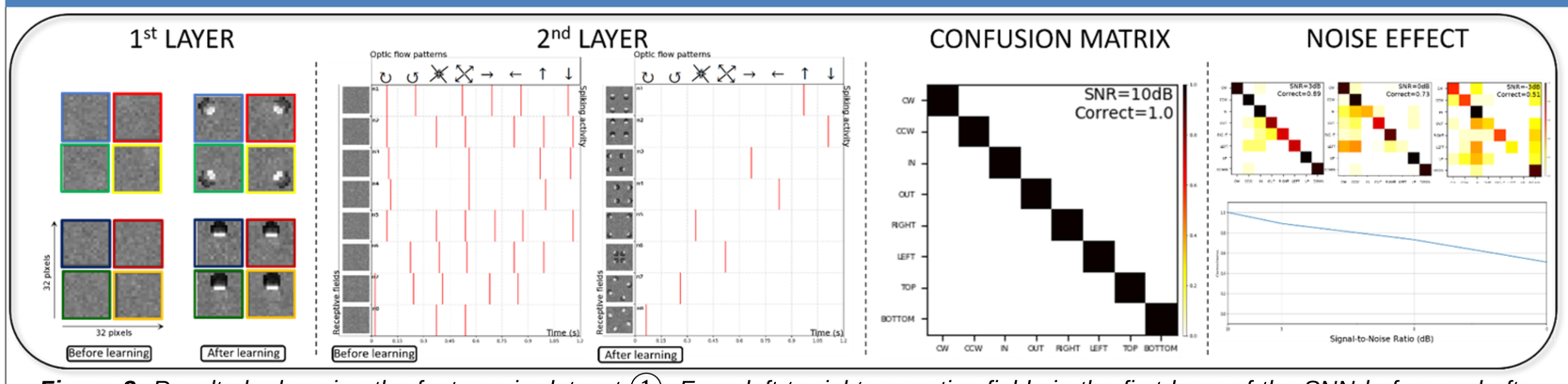

Figure 2: *Results by learning the features in dataset ①. From left to right: receptive fields in the first layer of the SNN before and after learning; spiking activity of the second layer and its receptive fields associated with the presented patterns before and after learning; the associated confusion matrix obtained with a classification method presented in (Diehl and Cook, 2015); the robustness of the SNN when the inputs for learning present different levels of noise: SNR=10, 3, 0, and -3 dB, top: confusion matrices for the SNR=3, 0, -3 dB respectively, bottom: chart of the correctness of the SNN given the different SNR.*

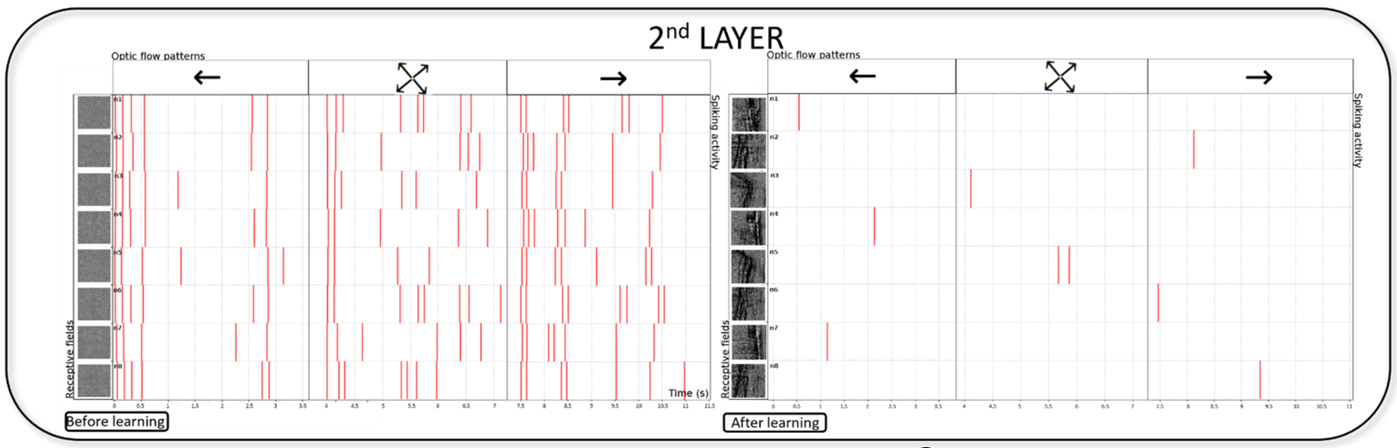

Figure 3: *Resulting spiking activity from the SNN after learning the features in dataset ②. From left to right: receptive fields of neurons in the second layer of the SNN before learning with their associated spiking activity when presented the 3 motions found in the dataset; the same receptive fields after learning when represented the same 3 motions and their spiking activity.*

For both datasets, learning led to artificial neurons with specific spatio-temporal structures. Selectivity in the second layer is generally broader than in the first one as observed in the primate visual system, notably in areas MT and MST (Beyeler et al., 2016).

For dataset ①, neurons in the first layer became selective to local motion information while neurons in the second layer became selective to optic flow components (translational, radial and rotational patterns). Eight different patterns emerged describing the ones presented to the network thanks to the detection of local motion patterns combined into global motion ones through the two stages of the network. Figure 2 shows the receptive fields of the neurons before and after learning and their spiking activity when the eight different optic flow patterns are presented, and the robustness of the SNN to different levels of noise.

For dataset ②, as shown in figure 3, neurons in the second layer became selective to different motions found in the event video input. These motions can be described as leftward, forward, and rightward motion depicted by the arrows. Before learning, neurons are spiking whatever the motion. After learning, the same neurons captured motion patterns in their receptive fields and are spiking accordingly.

TAKE-HOME

Our work suggests that a simple SNN equipped with a Hebbian rule, when unsupervisely trained under naturalistic conditions, is able to capture motion selectivity.

The observed properties of the artificial neurons are consistent with those in the primate and attest the development of optic flow selectivity.

REFERENCES

- Beyeler, M., Dutt, N., & Krichmar, J. L. (2016). 3d visual response properties of mstd emerge from an efficient, sparse population code. *Journal of Neuroscience*, *36*(32), 8399-8415.
- Bichler, O., Querlioz, D., Thorpe, S. J., Bourgoin, J. P., & Gamrat, C. (2012). Extraction of temporally correlated features from dynamic vision sensors with spike-timing-dependent plasticity. *Neural networks*, *32*, 339-348.
- Chauhan, T., Masquelier, T., Montlibert, A., & Cottereau, B. R. (2018). Emergence of binocular disparity selectivity through Hebbian learning. *Journal of Neuroscience*, *38*(44), 9563-9578.
- Mueggler, E., Rebecq, H., Gallego, G., Delbruck, T., & Scaramuzza, D. (2017). The event-camera dataset and simulator: Event-based data for pose estimation, visual odometry, and SLAM. *The International Journal of Robotics Research*, *36*(2), 142-149.
- Diehl, P.U. and Cook M. (2015). Unsupervised learning of digit recognition using spike-timing-dependent plasticity. *Frontiers in Computational Neuroscience*, 9:99.