- APROVIS3D -

Analog PROcessing of bioinspired VIsion Sensors for 3D reconstruction

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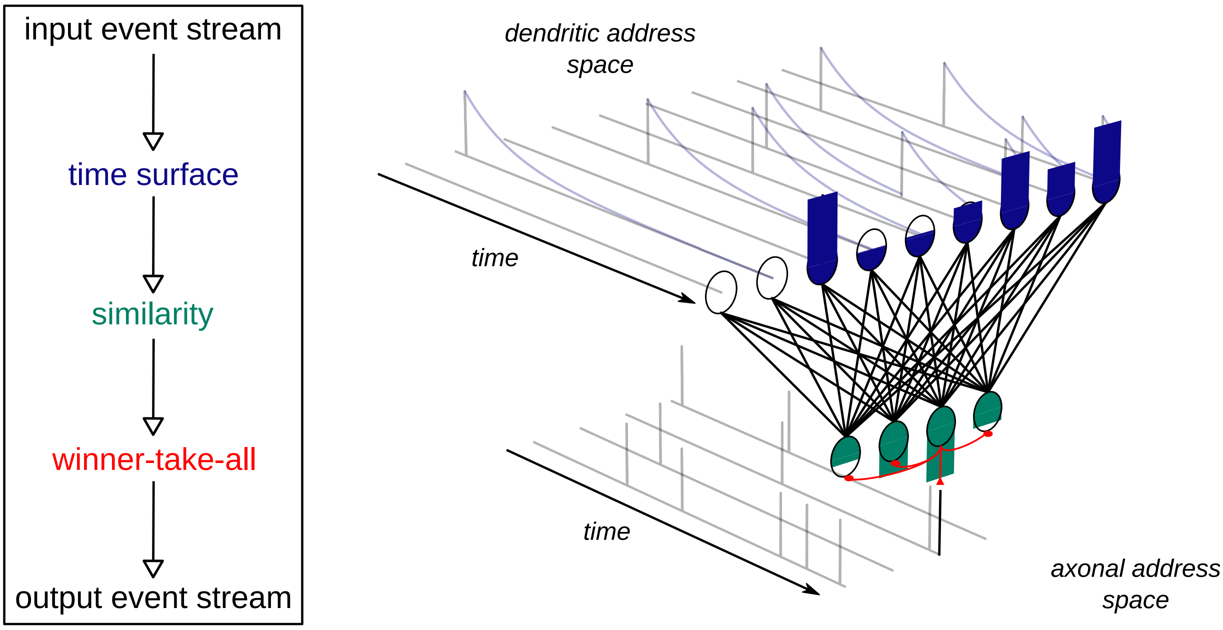

Figure 1: Illustration of the core computation made within one layer of the HOTS algorithm. On the top of the plot, we show the dendritic stream of events convolved by an exponential decay which forms the time surface. Time surfaces are computed at the timestamp of each event/spike. The time surface at present is represented with the colored bar plot on the top. In the vertical slice, computations made within one layer at time t_i are illustrated. The time surface is compared to all the kernels of the layer with the similarity measure resulting in the membrane potential of the postsynaptic neuron represented in green. As an illustration, the layer contains only 4 neurons associated to 4 different kernels and with 10 dendritic inputs. At last, a winner-take-all rule (or argmax non-linearity) will choose at time t_i the most activated neuron. This will emit a spike and prevent the others from being activated through lateral inhibitions (in red). Note that for each event as input of the layer, a new event will be emitted with the same timing as the incoming event.

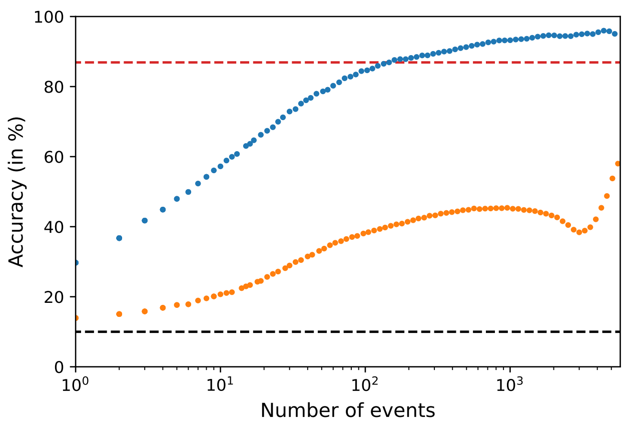

Figure 2: Online classification performance on the N-MNIST dataset. We show the average accuracy computed with respect to the number of events since the beginning of the stream. The red horizontal dashed line shows the classification performance for the offline method described in [Lagorce et al. 2017.](#) In blue, we show the results for our online classification algorithm and in orange, as a control, a MLR applied on the raw event stream (without passing through the HOTS network)

TABLES

1. Introduction

We developed a SNN-based machine learning adapted for DVS signal. To achieve this, we extended an existing event-based algorithm [Lagorce et al. 2017], which introduced novel spatio-temporal features as a Hierarchy Of Time-Surfaces (HOTS). Built from asynchronous events acquired by a neuromorphic camera, these time surfaces allow to code the local dynamics of a visual scene and to create an efficient event-based pattern recognition architecture. Our first contribution was to add a homeostatic gain control on the activity of neurons to improve the learning of spatio-temporal patterns. A second contribution is to draw an analogy between the HOTS algorithm and Spiking Neural Networks (SNN). Following that analogy, our last contribution is to modify the classification layer and remodel the offline pattern categorization method previously used into an online and event-driven one. This classifier uses the spiking output of the network to define novel time surfaces and we then perform online classification with a neuromimetic implementation of a multinomial logistic regression. Not only do these improvements increase consistently the performances of the network, they also make this event-driven pattern recognition algorithm online and bio-realistic. This work was submitted to the journal IEEE Transactions on Pattern Analysis and Machine Intelligence and is available as a preprint.
This algorithm was tested on different datasets for symbol recognition and aim at being applied to coastline detection. This classification for each event can easily be adapted to a segmentation algorithm allowing to distinguish between the sea and the ground in order to locate the coastline.

2. Documentation

2.1 Applicable and Referenced Documents

#	Id	Description	Identifier (Ed Rev)	Date
AD1	FPP	Full Project Proposal	1.0	15.01.2019

2.2 Glossary and Terminology

Acronym	Definition
WP	Work Package
SNN	Spiking Neural Network
ML	Machine Learning
HOTS	Hierarchy Of Time-Surfaces
MLR	Multinomial Logistic Regression

3. Contents

3.1 Already existing event-based algorithm

Our method is based on an existing algorithm for event-based pattern recognition: Lagorce et al. 2017. In this work, the authors define time surfaces, a spatio-temporal object useful to treat the dynamics within the stream of events. With a hierarchical network able to learn prototypical time surfaces, the stream of events is transformed and used as an accumulation of spatio-temporal features to perform object classification. Its name stems from this Hierarchy Of Time Surfaces (HOTS). Major advantages are the event-triggered, online and unsupervised training of the hierarchical network and the transformation of the flux of events into a more complex flux of events allowing stacking of layers. This method is easily transferable to neuromorphic hardware considering the event-based nature of the computations.

3.2 Improvements

We identified two major drawbacks for this interesting algorithm: its learning of time surfaces is very sensitive to initialization and the classification is done offline, once the stream of events is treated by the network, by assessing the activation of the last layer through histogram comparison.
To deal with the variability in the clustering phase, we introduce a homeostatic gain control to regulate the activity of the neurons within one layer. Regarding the past activity of the neurons, one is prevented or encouraged to spike wether if it did or did not spike enough compared to neighbouring neurons. Results on the improvements linked to homeostasis are reported in a conference article: Grimaldi et al. 2021.
Then, we introduce a new classification layer that allows event-per-event online classification. The spiking mechanism of this classification layer is similar to one layer of the HOTS network and is illustrated in Figure 1. This always-on classifier is performed by a MLR and results are reported in this preprint: Grimaldi et al. 2022. In this article, we also demonstrate formally the relationship between this event-based, always-on classification algorithm and a SNN. Again, we show that this algorithm is implementable in a neuromorphic device.

3.3 Results

We report here, the classification results on a widely used dataset: the N-MNIST dataset which is a neuromorphic version of the well known MNIST dataset. We demonstrate that, with only a small number of events on the event stream, the performance of our method outperforms the previous offline one. By the end of the event stream, its performances competes with the state-of-the-art. This allows for ultra-fast object categorization and we plan on using this method for a segmentation task to detect the coastline.

3.4 Achievements and future plans

We developed a bio-inspired machine learning algorithm for event-based vision. By essence, this algorithm uses a SNN and is then implementable on a neuromorphic chip. Organized in a hierarchical structure, similarly to the visual cortex, our network is able to detect spatio-temporal prototypical patterns through *time surfaces*. These time surfaces make use of the delays between the last recorded events and offers an interesting method to process event streams. We aim at applying this method to a segmentation task between ‘ground’ and ‘sea’ patches that will lead to the detection of the coastline.