A Real-Time, Event Driven Neuromorphic System for Goal-Directed Attentional Selection

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Abstract. Computation with spiking neurons takes advantage of the abstraction of action potentials into streams of stereotypical events, which encode information through their timing. This approach both reduces power consumption and alleviates communication bottlenecks. A number of such spiking custom mixed-signal address event representation (AER) chips have been developed in recent years.
In this paper, we present i) a flexible event-driven platform consisting of the integration of a visual AER sensor and the SpiNNaker system, a programmable massively parallel digital architecture oriented to the simulation of spiking neural networks; ii) the implementation of a neural network for feature-based attentional selection on this platform.

Keywords: Attention, Selection, Neuromorphic, SpiNNaker, AER

1 Introduction

The neural processes which subserve attentional selection, and subsequently drive intelligent behaviour in animals, remain the subject of intense investigation within the field of computational neuroscience [1]. Precise spike timing is understood to play an important role in biological neural computation, for example, spike timing precision has been hypothesised to maximise the information transfer rate [2]. Event-driven platforms provide a natural architecture on which to simulate spiking neural networks. Traditionally, the control flow of a program is time-driven, while the flow in event-driven systems is dependent on the occurrence of events, while time is implicitly represented. Recently, sensors [3] [4], mixed signal VLSI chips [5] [6] [7] and parallel architectures [8] that are natively based on events have been developed. Such systems use Address-Event-Representation (AER), a lightweight protocol for asynchronous communication of spike events [9].

In this context, we present a configurable event-driven platform, composed of an AER visual sensor [4] and the SpiNNaker system [8], a programmable parallel machine oriented to the simulation of networks of spiking neurons. A significant feature of this system is that a direct connection (via an FPGA) between the AER sensor and the event-driven SpiNNaker system allows timing information in the spike-train to be preserved: spikes (events) are processed as they arrive, eliminating delays caused by both buffering and by the use of a host machine as a protocol translator [10]. While the SpiNNaker system offers a flexible event-driven platform for the real-time exploration of neural networks, which natively conforms with AER, SpiNNaker also allows neural network dynamics and topologies to be rapidly reconfigured using a high level language [11] [12].

An attentional selection system was implemented upon this neuromorphic platform. Visual cues consisted of oriented Gaussians, which were represented as locations on a retinotopic visual saliency map [13]; such features are the most basic representation in the hierarchical structure which subserves object recognition in the visual cortex [14]. The mechanisms of selection were inspired by the biased competition hypothesis of Duncan and Humphries [15], in which competition takes place between different representations of potential targets and goal-directed information from a particular working memory can be used to bias selection towards a particular target. Goal-directed signals were feature-based, whereby the activity of a working memory neuron represented the behavioural importance of attending to a particular visual feature. This work represents the first neuromorphic implementation of a feature-based selection system. Spatial bias has previously been implemented by injecting activity into a particular location on the visual saliency map [5].

The hardware setup is described in the next section, and experimental results are presented in Section 3; discussion and conclusions are presented in the final section.

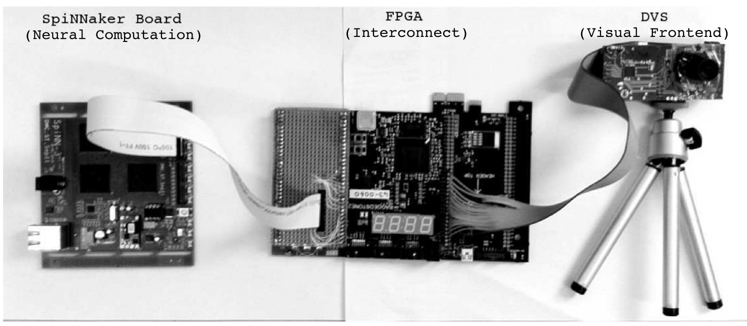


Fig. 1. Overview of the hardware setup: 4 SpiNNaker chips board (left), an FPGA translating the AER protocol between the two asynchronous systems (middle) and a DVS Silicon Retina (right)

2 Methods

2.1 Hardware setup

An image of the event-driven platform hardware is shown in Fig. 1.

Silicon Retina: the visual front-end is constituted by a Dynamic Video Sensor (DVS) silicon retina, an asynchronous sensor which provides spike events encoding the address of pixels undergoing a contrast change [4]. This approach lies in opposition to the more traditional method of sending entire frames to provide fast (3 μs latency) data-driven contrast detection at a wide range of illuminations. The sensor is capable of transmitting from 1 Keps to 20 Meps (events per second).

SpiNNaker System: neural processing is carried by 4 SpiNNaker chips, offering an event-driven digital platform that can interpret incoming events as neural spikes and inject them in the neural system. Each SpiNNaker chip is equipped with 18 programmable ARM9 cores embedded in a configurable packet-switched asynchronous network-on-chip [16], based on an on-chip Multicast (MC) Router capable of efficiently handling one-to-many communication of spikes (MC packets), and linked to 6 neighbours through fast asynchronous links. The system is designed to scale up to 65536 chips (each consuming 1W) and a million cores [8], offering a flexible, power-efficient platform for large-scale real-time modelling. Each SpiNNaker chip natively responds to events occurring in the network, and is therefore able to process information arriving from event-based sensors attached to its asynchronous links, provided the AER protocol is translated correctly.

Interconnection: retinal events are translated into asychronous spike trains in the neural network: as soon as an event is emitted from the silicon retina, it is translated into a SpiNNaker spike by a Xilinx SPARTAN-6 FPGA and injected into the system directly on the fast on-board interconnect, via one of the six asynchronous links available on each SpiNNaker chip.

Configuration: two levels of virtualisation allow a transparent mapping between the silicon retina and the SpiNNaker system. From a hardware point of view the DVS is mapped as a virtual SpiNNaker chip, injecting spike events into the network-on-chip. To the neural network, the silicon retina is represented as a *SpikeSource Population* by the mapping tool [12]. As with the rest of the neural network, the SpiNNaker system allows configurable *Projections* to this neural population using a high-level language such as PyNN [11].

2.2 Network Description

Fig. 2 contains a diagram of the implemented network [17], which was inspired by the primate visual system. In the first layer, neurons responses were selective to stimulus orientation, in a similar manner to neuronal responses in cortical area V1 [18]. The *pooling & competition* layer subsampled the activity of neurons with the same preferred orientation (implementing a *localmax* function, in a manner similar V2 complex cells [14]), while local competition between

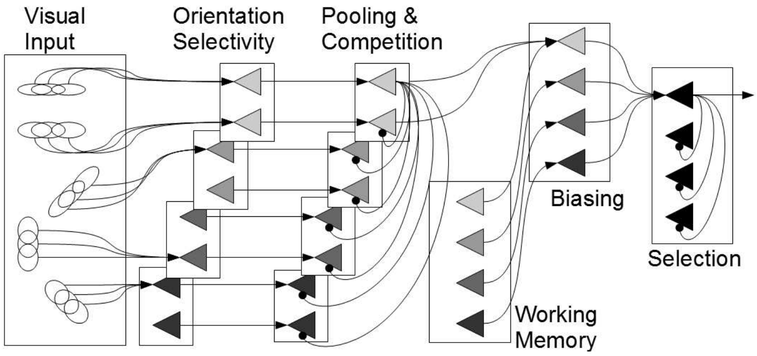
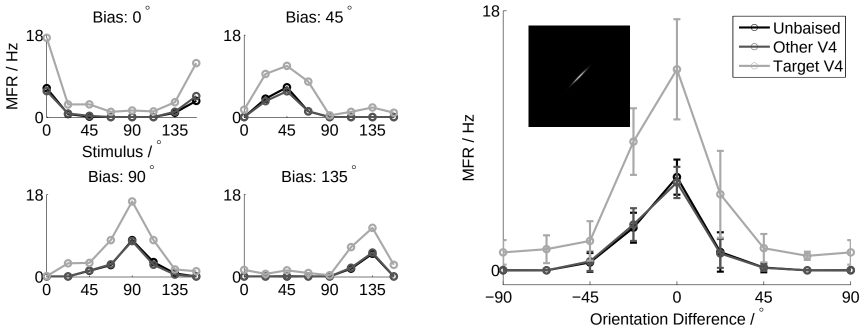


Fig. 2. Overview of the neural network; shaping indicates preferred orientation (black neurons do not encode orientation information). Complete projections from only the palest neurons are shown for clarity. Neurons are represented by triangles, arrows represent excitatory synapses and circles represent inhibitory synapses.

neurons with different preferred orientations sustained the activity of neurons whose preferred orientation matched the stimulus, and suppressed activity relating to non-matching neuronal responses. Four neuronal populations in the *working memory* layer encoded the goal of selecting a stimulus with a particular orientation. Activity in this layer was determined by a set of external biasing currents. In primates, visual search goals are believed to be encoded in the activity of the dorso-lateral prefrontal cortex neurons [1]. The *biasing* layer received combined activity from the *pooling & competition* layer and the *working memory* layer, such that activity was maximised for stimuli of the desired orientation, provided they are also present in the visual field. These neurons are analogous to the neurons of cortical area V4, which receives a large input from working memory via the frontal eye fields [19]. Activity was pooled across all orientation maps in the *selection* layer to form a retinotopic visual saliency map (corresponding to the lateral intraparietal cortex, LIP area [20]), and competition between different retinotopic location in this layer resulted in the selection of a single target. Activity at this location (i.e. the target of attention) was maintained, while activity at other locations was suppressed. Attentional effects themselves were not included in this model.

The network was implemented with 1221 leaky integrate-and-fire neurons and 20530 current-based exponential synapses on a single SpiNNaker chip, and 128x128x2 DVS neurons that were binned to 16x16x2 spatial locations on the FPGA, while preserving the number of events received by SpiNNaker. Neurons were arranged in a square topology (14x14 in *visual input*, 10x10x4 in *orientation selectivity*, 10x10x4 in *pooling & competition*, 5x5x4 in *working memory*, 5x5x4 in *biasing*, 5x5 in *selection*). Both excitatory and inhibitory projections were allowed from individual neurons, though this is not observed in biology.



(a) (b)

Fig. 3. Experiment I; (a) Biasing layer mean firing rate (MFR) for neurons of each preferred orientation; (b) overlayed figure from (a) showing MFR as a function of the difference between preferred orientation and stimulus orientation. Each biasing layer is the most active when presented the preferred feature

3 Results

Experiment I tested interaction between working memory activity and the biasing layer for stimuli in isolation and Experiment II tested the ability of the *working memory* activity to bias selection towards a particular target in the *selection* layer. The stimulus consisted of a video of blinking oriented Gaussians, which were presented on an neutral background, Fig. 3(b) (insert) and Fig. 4.

3.1 Experiment I: Tuning Curves for Stimuli in Isolation

The *retina* was sequentially stimulated with 8 different oriented Gaussian functions ($\sigma = 4.0$ pixels, $\gamma = 0.2$ pixels). Each stimulus was presented for 5.0 s, stimuli blinked with a frequency of 0.5 Hz and *working memory* neurons fired with a mean frequency of 9.9 Hz.

Fig. 3(a) contains four panels, each of which shows the mean firing rates (MFR) of the *biasing layer* neurons when a particular *working memory* neuron was active and Fig. 3(b) shows the average tuning curve for all bias conditions. The MFR of the *biasing layer* neurons for the preferred orientation (palest) was compared with the MFR of the other *biasing layer* neurons (mid) and the MFR in the unbiased condition (dark). The MFR for the unbiased and non-preferred neurons was very similar, while the target neurons experienced an increased firing rate for all stimuli, indicating that the *working memory* successfully increased the gain for only the target neurons. Similar stimuli which were not explicitly represented by any orientation map also show increased activity.

3.2 Experiment II: Visual Selection Task

Stimuli consisted of two oriented Gaussian functions ($\sigma = 0.89$ pixels, $\gamma = 0.07$ pixels), one in the top left corner of the stimulus image, and one in the bottom right corner. Fig. 4(a). Two sets of orientations were tested at both positions: $\{0°, 90°\}$ and $\{45°, 135°\}$. Stimuli blinked with a frequency of 0.5 Hz and activity was recorded for 40 s. Fig. 4(b) shows the probability for a location becoming the attentional target in the unbiased condition (calculated as the ratio of the number of spikes at a location in *selection* to the total number of spikes in the *selection* layer). No selection bias was observed in this condition. Figs. 4(c) and 4(d) show the change in the selection probability when *working memory* was used to bias selection towards the feature in the top left corner and the bottom-right corner respectively. In both cases, selection was biased almost entirely towards the target feature. Fig. 5 shows that the firing of the two active group of *selection* neurons follows the activity of the *working memory* over time.

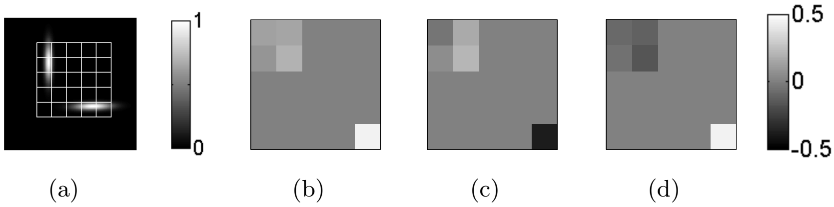


Fig. 4. Experiment II; (a) stimulus image; grid indicates the position of the neurons in the *selection* layer (b) firing probability across the whole *selection* layer for all pairs of unbiased stimuli; (c) change in firing probability (from (b)) when selection was biased towards the object in the top-left corner for all stimuli pairs; (d) same as before but towards the feature in the bottom-right corner

4 Discussion and Conclusion

The integration of the SpiNNaker system with an existing visual AER sensor exposes the advantage of a digital, programmable systems integration platform for neural computation. The platform presented in this paper forms a generic event-driven system, where neural networks may be rapidly implemented and configured. This processing platform benefits from the flexibility of SpiNNaker, in which neural network models can be described in a high-level programming language [11], making the hardware accessible to non-hardware experts [12]. Large-scale, real-time models can be rapidly developed and configured before casting them into their more efficient, but also less accessible and more expensive, task-specific analog counterparts [5] [7] [9].

A neural network model of feature-based attentional selection was implemented upon this processing platform. In this network, a feature-based working memory was used to drive attentional selection towards a target visual feature. This work represents the first neuromorphic implementation of a feature-based attentional selection system. In future, this work will be extended to include a more faithful model of the neural circuit which subserves attentional selection through the inclusion of modulatory top-down bias, as opposed to the additive effect which presented, and on attending complex stimuli learned from the composition of basic features discussed in this paper.

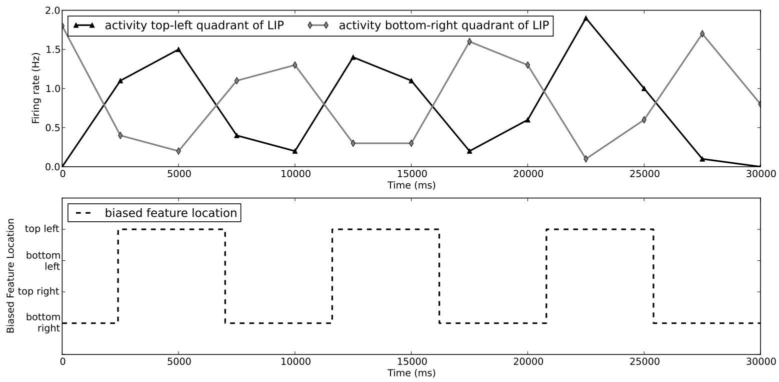


Fig. 5. Activity in LIP follows the movements of the biased stimulus.

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