Attentional modulation of firing patterns for spiking neurons

Holger Bosch Abderrahim Labbi Ruggero Milanese

Department of Computer Science
University of Geneva, Switzerland

1 Introduction

Computational complexity analyses suggest that completely feedforward models for visual perception may not be feasible [3]. A solution to this problem has been proposed in terms of a selective attention process which sequentially selects the most interesting region of the image for further analysis while the remaining parts are momentarily deferred.

One further motivation for a selective attention process is the fact that different features of the image are processed in different parts of the visual system in parallel. Therefore, if several objects are present in the image, the features of each object must be clustered together in order to allow proper object identification. This is known as the binding problem and one possibility to solve it is through the temporal modulation of the neuronal activity [2]. Units processing different aspects of the same object synchronize their activity while units processing other objects are desynchronized.

Only very few models based on spiking neurons (as opposed to the commonly used continuous oscillators) have been proposed to realize this temporal modulation by modifying the short-term frequency whereas the long-term frequency remains constant [1]. This is important since the information on the input is coded through the frequency of the neurons. Niebur et al. ([1]) propose to modulate the frequency with a periodic function, but they do not provide an explicit form. Moreover, they do neither provide the attentional signal nor investigate the synchronization of different units.

The model proposed in this paper provides the computation of the attention map, the generation of the modulation signal and an intra-object synchronization as well as an inter-object desynchronization. It aims to present a solution to the selective attention problem as well as the binding problem on the basis of biological plausible spiking neurons. The attentional signal groups several spikes into bursts which can be synchronized on their part.

The spiking neurons as well as the different components of the model are described in detail in the next section. Section 3 contains the simulation results along with their discussion and an outline of the ongoing work.

2 The Model

The model proposed in this paper consists of feature maps, one attention map and generators of the attentional feedback signal. Each of the components is described below in detail. All these maps are built using the same basic units which are described first.

Spiking neurons: the basic units of our system are spiking neurons. A neuron integrates its inputs until the resulting potential reaches the threshold. Then the neuron fires and the potential is reset to its resting level. After a refractory period the neuron restarts to integrate its inputs. A leakage term drives the neuron potential back to the resting level.

We chose a discrete version of spiking neurons with a time step of 0.5 ms. The threshold θ of each neuron equals $\theta = 1.0$ and the refractory period is two time steps. The only adaptable parameter is the leakage of the neuron which has a value between 0 and 1.

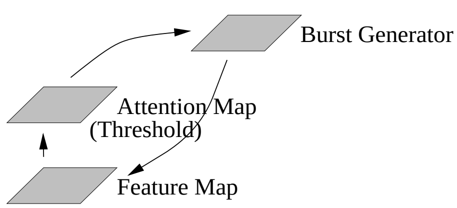

Figure 1: Global architecture of the system.

Feature map: each map is a two-dimensional array of spiking neurons which receives the intensity of the corresponding location of an input image as a constant input. These maps are meant to process the input image in order to extract information about color, orientation and curvature, although the present simulations only describe a simple map coding the intensity of the input image. The map contains 30×30 units which are not interconnected.

Attention map: the purpose of this map is the extraction of the most salient regions of the input image. In the general model, the map receives filtered input from the different feature maps using on-center off-surround receptive fields. The map will integrate these data and select finally the most conspicuous region.

In the current simulations a threshold is applied to the output of the feature map in order to extract the region of highest intensity. A local-excitation/global-inhibition connection scheme ensures that only one object is selected simultaneously at each time step (cf. [4] for an alternative solution to the same problem). The map contains 6×6 units with receptive fields of dimension 5×5 from the feature map.

Attentional Feedback: if the attention map has detected a conspicuous region, it feeds back a frequency modulation signal to the corresponding region of each feature map.

During the burst, any firing neuron receives a subthreshold input immediately after its refractory period, in order to drive the activity near the threshold. The result is a multiplication of the initial frequency by a constant factor during the burst.

Afterwards, the neurons receive a permanent negative input during a "silent phase" which strongly reduces spike emission in order to obtain the same long-term mean frequency.

The attentional feedback signal is repeated with a 20 Hz frequency until the attention signal fades at this region.

Frequency modulation signal generator: The module (see Figure 2) consists mainly of two parts corresponding to the excitatory and the inhibitory signals generated by the module. During the burst, a coincidence neuron continuously checks whether the corresponding neurons in the feature and attention map have fired. In this case, a subthreshold input is fed back to the neuron in the feature map after its refractory period. The end of the burst is signaled by the firing of a neuron measuring the burst duration. This signal stops the excitatory part of the module and activates the second which inhibits permanently the corresponding neurons in the feature map. At the end of the "silent phase", signaled by the firing of a specialized neuron, another coincidence neuron checks if attention is still present and the signal generator restarts in the affirmative case.

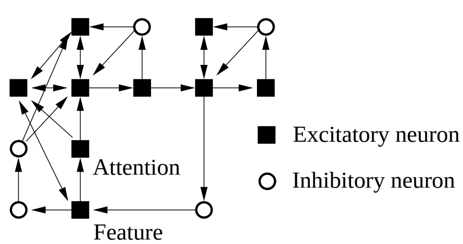

Figure 2: Sketch of the module generating the frequency modulating signal.

3 Simulation Results

The results presented below are obtained from simulations using an architecture consisting of one feature map of size 30×30, one attention map of size 6×6 and one 6×6 map of frequency modulation units. The input applied to the feature map is depicted in Figure 3.

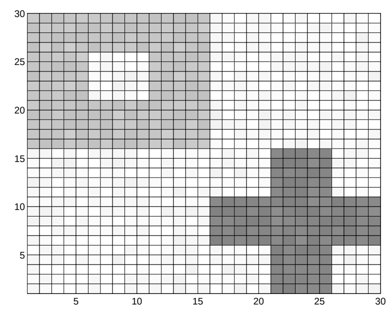

Figure 3: Input stimuli.

It contains two figures of different greylevels, which cover several receptive fields of the attention map. The entire input (objects and background) is noisy while the initial conditions of the system are chosen to be zero.

Figure 4 shows the number of spikes generated for the objects and the background during 250 ms. Since the intensity is higher in Object 1, the attention map detects this object first and activates the corresponding frequency modulation generators which produce a first burst for Object 1.

The short-range excitatory part of each attention map receptive field ensures that all the units affected by the object burst at the same time. On the contrary, the long-range inhibition part of the receptive field prevents Object 2 from entering the burst phase until the burst of Object 1 is over. The bursts of all parts of Object 2 are not completely synchronized since the signal-to-noise ration is lower for this object.

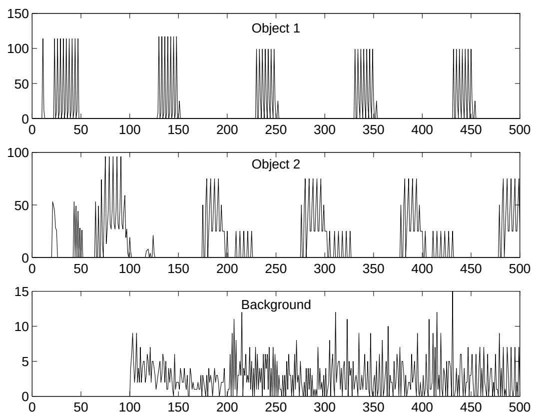

Figure 4: Bursting activity generated by the two objects and the background.

In conclusion, we presented a biologically-plausible model for an attention system, which is also a promising solution to the binding problem. One major advantage is the possibility to handle greylevel images, in opposition to the large majority of existing alternatives. Furthermore, several objects may be analyzed sequentially since the burst duration is much smaller than the following silence phase during which other objects may be analyzed before returning to the first object.

Ongoing work concerns the implementation of several feature maps and more sophisticated filter operations to extract the attention map. Furthermore, additional connections are being introduced between the feature maps in order to guarantee inter-map synchronization among units encoding selectively attended objects.

References

[1] E. Niebur, C. Koch, and C. Rosin. An oscillation-based model for the neuronal basis of attention. *Vision Research*, 33(18):2789–2802, 1993.

[2] W. Singer. Synchronization of cortical activity and its putative role in information processing and learning. *Annu. Rev. Physiol.*, 55:349–374, 1993.

[3] J.K. Tsotsos. Analyzing vision at the complexity level. *Behavioral and Brain Sciences*, 13:423–469, 1990.

[4] D. Wang. Emergent synchrony in locally coupled neural oscillators. *IEEE Transactions on Neural Networks*, 6(4):941–948, July 1995.