The Coherence Theory:
Simple Attentional Modulation Effects

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Abstract

We present a novel method of achieving attentional modulation effects, based on the spatial coherence of the stimulus. Such modulator effects are known to occur also at low levels in the visual cortical pathway. We use temporal coding rather than rate-based coding. The temporal coding is biologically plausible and also proves to be noise resistant. Synchrony and asynchrony are estimated in an ultra-rapid fashion, the competition between them leading to attentional modulator effects. Our "Coherence Theory" as a new way of understanding neural processing offers the theoretical framework for our findings.

Keywords: Attentional modulation; Coherence; Temporal Coding; Correlation; Decorrelation; Spiking neurons; Shunting inhibition.

1. Introduction

The "Coherence Theory" [8] has emerged as a new way of understanding neural processing on the visual pathway. The main driving force, in its context, is coherence. However, coherence is a general and subjective principle. There are many ways to interpret and understand coherence. Coherence is also very much related to the context of the processes that infer or observe coherent aspects of the world. At the lowest levels of visual processing, the primary layers on the ventral pathway (like V1, V2) have a small receptive field. Thus, the context of simple cells is their small receptive field (up to a few degrees [1]). We try to show that simple mechanisms, that rely on ultra-rapid synchronization can lead to the estimation of local, spatial coherence. More, we believe that such inferred local coherence could play an important role in the modulation of attention in hyperacuity and preattentive visual search.

Recent studies show that attentional modulator effects emerge also at the first levels of processing, in the primary visual cortex [11]. Attention and eye position may not be directed to the same location [10], suggesting that specific mechanisms should exist to allow selective modulator effects to occur. The question is what kinds of mechanisms are involved, how could these mechanisms arise and what is the time scale of processing. We believe that attentional modulation is very complex, having not one but many origins and that some primary, low level, mechanisms allow us to rapidly discriminate and achieve pop-out effects with or without the involvement of superior, conscious, processes. As a consequence, there might be a link between the

ability to detect illusory contours, bind features together, eliminate noise and achieve attentional bias. Ultra-rapid coherence estimation could lead to preattentive modulator effects.

We will try to show that a simple architecture of biologically plausible spiking neurons can indeed achieve modulator effects, in a bivalent manner (attend to a coherent stimulus or attend to the incoherent surround that is noise). Also, we show that under heavy noise, the system is able to detect a coherent line, while no orientation selectivity was included in the modeling of simple cells.

2. The "Coherence Theory"

The tasks achieved by the visual system are very complex while the speed of achieving these tasks is amazing [12]. In recent years, overwhelming evidence show that very complex processes occur even at the lowest levels of visual cortical processing. Contour integration [4], illusory contour approximation, border-ownership coding [14], curvature estimation [9], attentional modulation [11] are just a few examples. However, at this time, we are not able to explain why and certainly not, how. We formulated a principle that tries to unify all these findings under a single theoretical framework: the "Coherence Principle".

The coherence principle in the visual nervous system's context is the following: *the nervous system is a coherence detector that extracts, processes, enhances and infers coherent aspects of the real world by the means of two mechanisms: correlation and decorrelation.*

Our theory mainly relies on the paradigm of temporal coding. Correlation and decorrelation emerge from synchronization and desynchronization processes on an ultra-rapid time scale. Populations of neurons are interconnected by large synaptic trees that, in our simple model, follow a retinotopic organization. Among the functionally relevant neurons, populations of interneurons exist. The interneurons form synapses close to the cellular body of functional neurons, achieving shunting inhibition effects. We take into account each individual spike and simulate millisecond processes that allow shunting inhibition to influence the overall activity of functional cells. Due to strong shunting inhibition, some cells are able to estimate the degree of firing time synchrony of their afferent cells. Synchronized assemblies can thus be detected.

3. The model

3.1. General architecture

Previous studies [5,7,8] allowed us to construct a simple, biologically plausible architecture in order to test the way spatial coherence can lead to attentional modulation effects. Separate populations of neurons encode either synchrony or asynchrony in the stimulus pattern. Synchrony builds up ultra-rapidly, by the means

of lateral interaction [6]. Predominantly, lateral interaction is inhibitory, the receptive field (RF) profile resembling with a center-surround structure (narrow center excitation and wide, silent surround suppression). Such a RF profile fits very well biological observations and maybe asymmetric suppression could also play an important part in achieving various functions and detecting coherence [13]. We used V1, V2 and V4 cells with no orientation preference. A sketch of the model is presented in **Fig 1**.
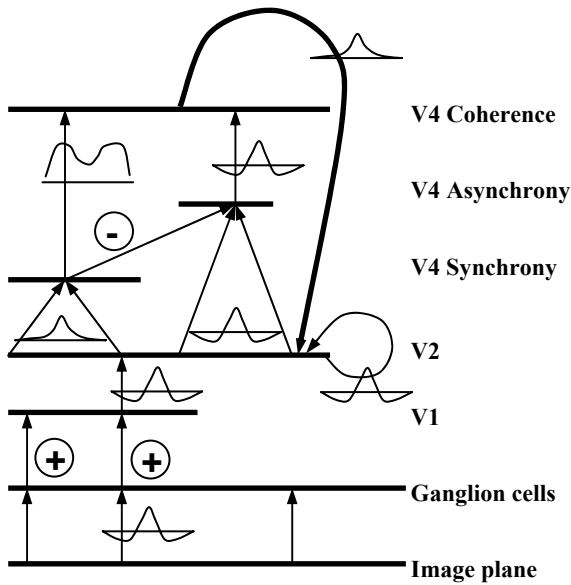

Fig. 1. The architecture of the model. The receptive field profiles are shown on connections between layers. "+" and "-" denote simple constant excitation or inhibition. No directional preference is included in the model.

We excluded orientation preference intentionally to prove that spatial coherence can be estimated in a robust manner by the synchronization effects. However, orientation preference might improve the model's performance.

3.2. Experimental setup

Each layer consists of a neural map having the same size as the input image. The input images used were 100x100 pixel grayscale bitmaps with 256 levels of gray.

We used simple, spiking, integrate-and-fire neurons [2,3,5,7,8]. Neurons receive input spikes and increase their internal activity, until they reach a fixed threshold. The parameters of the neuron fit the biological evidence. The resting potential is –65 mV and the threshold –45 mV. No refractory period included. We use rank order coding as neural code and every neuron has 3 parameters: an activation level (**U**), a synaptic modulation (**M**) and an instantaneous sensitivity (**S**). The activation level determines the moment of spike generation while the synaptic modulation and the sensitivity, both model the fast shunting inhibition. The update rule states that for every incoming spike, the activation level of the neuron is updated with the synapse

weight modulated by the instantaneous sensitivity of the neuron. The sensitivity is then decreased using the synaptic modulation factor [5] ($M \in (0..1)$).

$$U^{(t+1)} \leftarrow U^{(t)} + S^{(t)} \cdot W[\textbf{current\_synapse}] \quad (1)$$

$$S^{(t+1)} \leftarrow S^{(t)} \cdot M \quad\quad\quad\quad\quad (2)$$

The value of the synaptic modulation factor (M) determines the strength of shunting inhibition (as M approaches 0, shunting efficacy increases).

The architecture implemented makes extensive use of the retinotopic organization of some parts of the visual system. Synapses are modeled as connection kernels, with variable size, that characterize the entire connection between two neural maps. Three types of kernels were used to implement the architecture in **Fig. 1**: center-surround kernels (**C-S**), gaussian kernels (**G**) and simple, constant kernels (**K**).

$$C-S(x,y) = \textbf{onGain} \cdot e^{\frac{-(x^2+y^2)}{2\cdot\sigma_1}} + \textbf{offGain} \cdot e^{\frac{-(x^2+y^2)}{2\cdot\sigma_2}} \quad (3)$$

$$G(x,y) = \textbf{Gain} \cdot e^{\frac{-(x^2+y^2)}{2\cdot\sigma}} \quad\quad\quad\quad\quad (4)$$

$$K(x,y) = \textbf{Gain} \quad\quad\quad\quad\quad\quad\quad\quad (5)$$

Usually the **onGain** and **offGain** have different signs, depending on the type of center-surround effect (center-ON-surround-OFF or center-OFF-surround-ON). Depending on the value of **Gain**, which stands for the synapse weight (5) or at least the magnitude of the gaussian (4), excitatory or inhibitory effects can me modeled.

Ganglion cells were modeled as 3x3 unit center-ON-surround-OFF kernel, with $\sigma_1 = 0.18$, $\sigma_2 = 0.53$, and normalized to 0. Unless specified, modulation factors (**M**) were set to 1 by default. Constant gains for connecting ganglion cells with V1 cells were 21 mV / spike. V1-V2 connections are modeled by a center-surround kernel, with $\sigma_1 = 0.33$, $\sigma_2 = 1.66$, **onGain** = 65 mV, **offGain** = -90 mV. Lateral interactions in V2 are modeled by using the same kernel. Synaptic modulation effects are weak in V2 (**M** = 0.99) and have normalization purpose. V4 synchrony detectors are connected with V2 by using a gaussian kernel, with σ = 1.66 and **Gain** = 70 mV. Moderated synaptic modulation effects are included, **M** = 0.9. V4 asynchrony detectors are connected to V2 by means of a center-surround kernel, with $\sigma_1 = 0.33$, $\sigma_2 = 1.66$, **onGain** = 40 mV, **offGain** = -100 mV. Also, there is a strong inhibitory connection with V4 synchrony detectors, modeled as a constant kernel, with hyperinhibition of -100 mV / spike. Modulator effects at synaptic level induce very

strong shunting inhibition, M = 0.2. The final map is connected to the synchrony and asynchrony detectors by the means of a center-surround kernel, with σ_1 = 1, σ_2 = 1.66, **onGain** = 50 mV, **offGain** = 150 mV, and a center-surround kernel with σ_1 = 1, σ_2 = 1.66, **onGain** = 150 mV, **offGain** = -50 mV respectively.

Top-down modulation from the final map to V2 is achieved by using a center-surround kernel, with σ_1 = 1, σ_2 = 1.66, **onGain** = 30 mV, **offGain** = -10 mV.

4. Results

We tested the system by presenting noisy images where the coherent object is a line. Subjective estimation of the pop-out effect has been made and the amount of noise has been increased to a limit where coherent spatial groups emerge due to the random noise (up to 80% of random noise). The stimulus images and modulator effects are presented in **Fig. 2**.
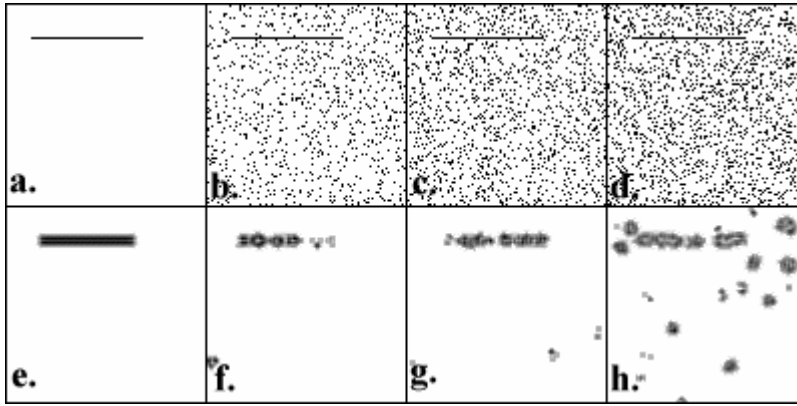

Fig. 2. Test images and attentional pop-out effects due to spatial coherence. Progressive random noise is included as follows: **a.** 0%, **b.** 40%, **c.** 60%, **d.** 80%. Attentional pop-out modulation effects for each of the stimulus images (**a. - d.**) are presented in **e. - f.** respectively.

Subjective estimation allows human subjects to concentrate on the spatially coherent features (like the line) or on the surrounding noise. Such a mechanism could correspond to a context switch. Our coherence framework captures naturally such aspects since we mentioned that coherence is subjective. The relevant criterion for the context is in our case the spatial extent of the stimulus. When the subject is interested to isolated points, the context is switched towards shrinking the spatial extent of context integration. In our particular model, the balance between synchronous and asynchronous inputs could play the role of the context switching mechanism. A simple context switch is presented in **Fig. 3.**
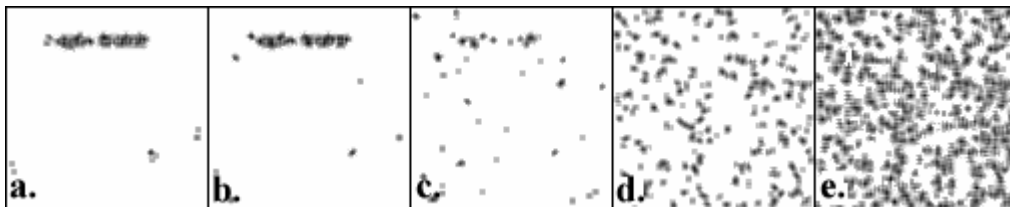

Fig. 3. Context switch and attentional modulation. As the synchronous inputs are being inhibited and the asynchronous inputs facilitated, the background noise effect is reinforced. The balance between synchrony and asynchrony is presented in **Fig. 4.**

We mention that the synchronization effect is obtained under 10 ms equivalent biological timing.
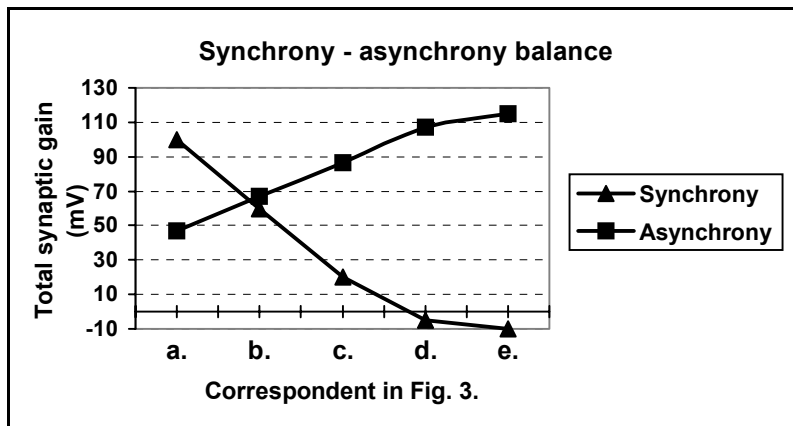
Fig. 4. Synaptic gain balance during context switch.

Modulator effects in our model emerge after only 50 ms equivalent biological timing. Such rapid, coherence based attentional modulation, could play an essential role in achieving object based attention effects.

Acknowledgements

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