COMPUTATIONAL ANATOMY IN LOW-LEVEL VISUAL PROCESSING

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Abstract

From the examination of neurophysiological data concerning all sensory areas and especially of the striate cortex it emerges that the computational properties of brain in visual processing might be related to its structural organization. In this paper, we attempt to capture the structural and anatomical rules that might underlie such computational properties; specifically, we focus our attention on low-level visual processing. In this context we consider optimal feature-extractors and neuromorphic architectures for simple visual tasks.

1. Introduction

The comprehension of a natural scene, the recognition of objects, or simply image segmentation involve different levels of computation. One can distinguish between *low-level processing*, mainly driven by sensory data, and *high-level processing*, mainly driven by a priori knowledge. Nevertheless, there is a not clear boundary between these two levels and all stages of computation are necessary to accomplish visual perception. Indeed, perceptual tasks end in high-level associative areas, where different information from all sensory areas integrate themselves to achieve consciousness, but low-level processing plays a relevant role, since a rough representation of visual information can affect the effectiveness of subsequent cognitive processes. Several attempts have been made in the past decades in order to understand how brain computes visual information, considering both single-cell and global activity. At a single-cell level, it has been suggested [1] that the visual scene is analyzed by a set of feature-selective cells that respond optimally to specific stimuli (*trigger-features*); others [2] proposed that local Fourier analysis might provide the basis for visual representation and postulated the existence of spatial-frequency channels. At a global-level, perceptual computation has been formulated in terms of *perceptual waves*, and, more recently, in terms of coherent oscillations [3] and synchronization of electrical activity [4]. Although there is a supporting evidence for each of these models, none of them is sufficient on its own to capture the nature of neural representation of visual world. Moreover, the functional architecture of the visual system, from retina up to the striate cortex [5], hints that the efficacy of brain to create its perceptual code might be in its structure itself. Hence, the understanding of the general properties of visual processing requires the comprehension of the *computational anatomy* of the brain, a term first introduced by Schwartz [6], to indicate all anatomical facts governing computation, including columnar organization [5], retinotopic mapping, but also lateral inhibition, clustered connectivity, feedback loops, etc. [7]. According to such principles, in this paper we consider some possible strategies of cortical computation related to the structure of interconnections. We describe two examples of computational anatomy that can lead to formal neural networks and provide solutions for the design of sensorial hardware devices.

2. Computational Anatomy in the Striate Cortex

The primary visual pathway (retina, lateral geniculate nucleus (LGN) and striate cortex) is basically a hierarchical network, organized in a laminar fashion. Each element can be characterized by its receptive field (RF), individuating the area of the visual field in which luminous stimuli best elicit the neural response. Ascending in the visual pathway, RFs become more and more complex and information is coded with increasing abstraction, from the retina, where signals are merely measures of contrast, up to the striate cortex, where neurons handle symbolic information. Almost the totality of cortical neurons responds optimally to moving or flashing oriented bars and gratings, and, according to the increasing non-linear characteristics of their responses, we can distinguish *simple*, *complex* and *hypercomplex* cells [5]. At the cortical level, neurons are highly organized so that assemblies of neurons sharing nearly the same orientation preference are grouped together (forming the so-called *orientation columns*) and, on a larger scale, a systematic shift in the preferred orientation reveals a functional regularity of the orientation preference (*orientation maps*). One complete set of orientation columns, spanning all orientations, is called *hypercolumn* [5]. Besides by feed-forward connections, that provide to each cortical layer the main input, such layers are vertically intercoupled also by means of feedback connections. Furthermore, the presence of horizontal clustered connectivity [7] provides interchange of information also among different columns. The modular organization of the visual cortex ensures segregation of image information content and the presence of retinotopic mapping maintains topological correspondence between the retinal plane and the cortical representation [6]. Thus, intracortical processing acquires a semantic meaning and plays a decisive role in the definition of the properties of single neurons.

3. Applications to Artificial Neural Networks

Synthesis of linear cortical operators A fact emerging from anatomy, states that the computational characteristics of each neuron are not independent of the ones of other neurons laying in the same layer, rather, they are often the consequence of a collective behavior of neighboring cells. More specifically, we can observe a sort of superposition of feed-forward and feedback contributes, that allows a description of the visual pathway at different levels of abstraction. At each level, we can identify *components* or computational primitives due solely to feed-forward connections (afferent projections) and the properties not found in the components of a given level can emerge from their organization and their interactions at a higher level. In accordance with such principles, several researchers [8 9] have investigated the origin of cortical RFs, and obtained neural models of optimal feature-detectors. By analogous considerations, we have recently developed [10] a linear framework for analytic evaluation of simple cell RFs (see Fig. 1). We have assumed that functional projections of LGN afferent neurons provide to cortical cells only a weak bias in orientation and the final profiles of the RFs are mold by inhibitory mechanisms within the cortex. Recurrent inhibition is modeled by a convolution operation, the shape of its kernel depends on various schemata such as *cross-orientation inhibition* [11], and *circular inhibition* [8]. By evaluating receptive field profiles after intracortical inhibition with different orientation maps, we verified that the inhibitory action improves feature-selectivity of cortical cells and, under particular conditions, leads to periodic Gabor-like RFs similar to the one observed experimentally by many researchers [12]. Since 2-D Gabor functions maximize space and spatial-frequency selectivity [13], these results suggest that the neural paradigms of Fig. 1 can be followed for the synthesis of artificial spatial operators for image analysis. *A neuromorphic architecture for texture analysis* Visual information processing and representation, is also related to cortical modularity. Indeed, the presence of separate modules for different subtasks provides an high degree of flexibility, allowing neural architecture to be optimized for particular types of computation. Cortical modularity has suggested numerous models [14] [15] in which different information on orientation, direction of movement, contrast and occlusion boundaries of a stimulus are mapped in dedicate modules, and then integrated by recursive signaling between separate maps along ordered anatomical connections [15] or cooperative-competitive feedback loops [14]. Exploiting the modular organization of orientation-selective cells (see Section 2), we developed [16] an architectural model for texture segregation in which the fundamental module is an hypercolumn collecting simple, complex and hypercomplex cells. In each module, computation is carried on in two distinct phases: first the image is preprocessed by a set of oriented filters having different orientations, phases and contrast sensitivity, then, non-linear competitive (inhibitory) and cooperative (excitatory) mechanisms among cells in the same module and belonging to nearby modules, refine simple cell responses and create the outputs of complex and hypercomplex cells. A sketch of the network architecture is depicted in Fig. 2. Fig. 3 illustrates the performance of this architecture in the processing of a natural textured image. It is worthy to note that replicating the same module many times over allows local stereotyped computations to be carried out in a massively parallel way. Thus, by mapping neural computation directly on the electrical variables that describe the state of the network [17], such architectures result particularly suitable for VLSI implementations.

4. Discussion and Conclusions

The main questions that arise in visual neuroscience are how brain represents and processes visual information and how it solves the problem of controlling information flow. The organization of visual pathway and especially of striate cortex, suggests that the structure itself of neural circuitry might be a powerful computational solution. Thus, according to Schwartz's terminology [6], we have referred to computational anatomy as the basic paradigm underlying computation. Taking on board the richness of biological structures (such as inhibitory mechanisms, feedback loops, clustered connectivity, cortical modularity, etc.), architectures that deal with neural microcircuits are introduced to model arrays of highly interconnected neurons. Some investigators disagree with the general view that functional organization of sensory areas is really important for computation, asserting that such organization arises as a byproduct of the rules of synapses formation. Anyway, studying the basic mechanisms and circuits available for biological visual processing, one can obtain powerful computational solutions for complex visual tasks in machine vision.

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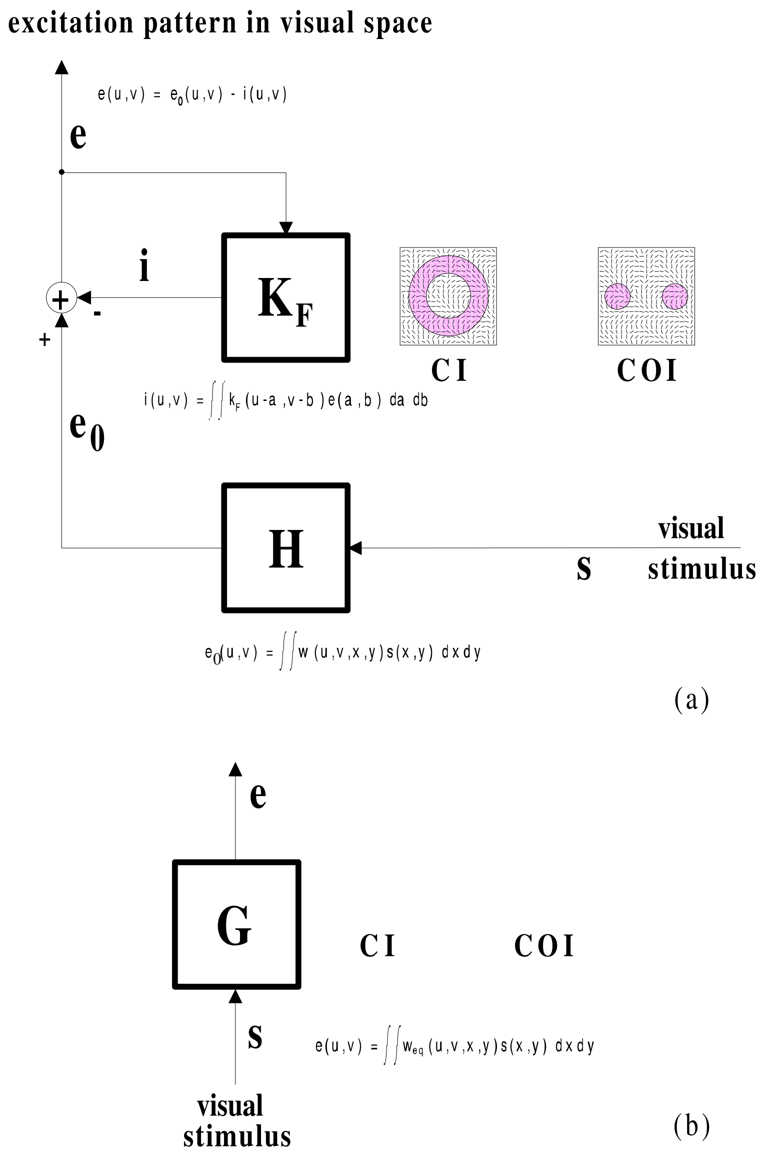

Figure 1: (*a*) A block diagram representation of visual cortical processing. **H** represents the computation from retina up to the first layers of visual cortex, before intracortical processing. **H** acts directly on the visual input s through oriented RFs as the one depicted by the side of **H**; the spatial arrangement of oriented RFs characterizes the specific orientation map. The feedback pathway, block $\mathbf{K_F}$, models intracortical recurrent inhibition, thus contributing to the activity of cortical cells. More specifically, the profile of kernel $\mathbf{K_F}$ models the linear spatial coupling among cells, according to various inhibitory schemata, e.g. *cross-orientation inhibition* (COI), and *circular inhibition* (CI), as depicted by the side of side block $\mathbf{K_F}$. The system can be reduced to the one depicted in (*b*) where **G** represents an equivalent integral operators that takes into account also recurrent inhibition. The resulting RFs for the inhibitory schemata are shown by the side of **G**.

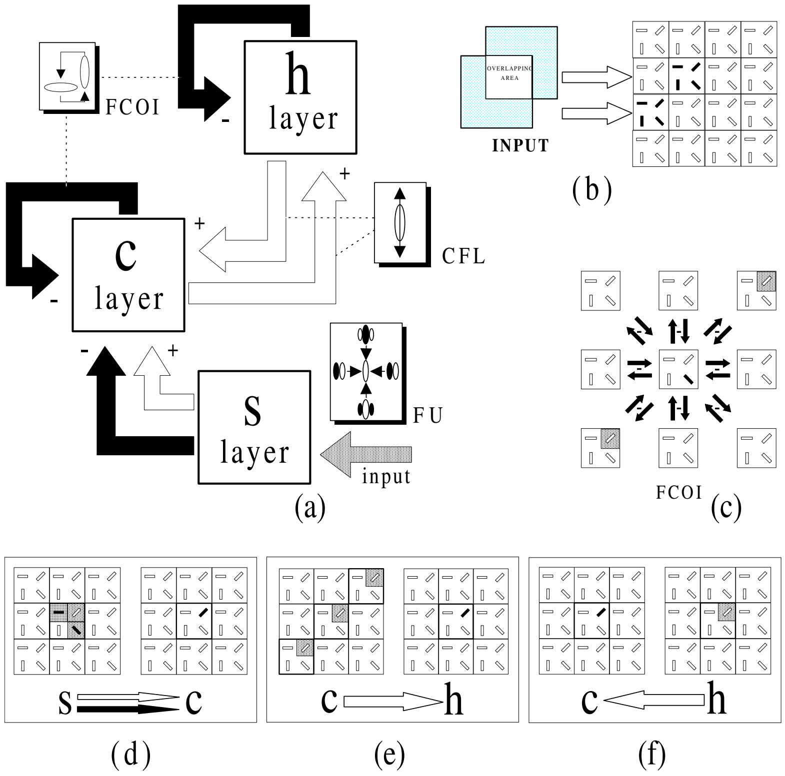

Figure 2: Architectural overview of a neural network for texture analysis. Three classes of cortical layers are considered: simple (s), complex (c), and hypercomplex (h). The first layer (s-layer) extracts oriented textured elements, the second (c-layer) increases sensitivity to texture difference and the last one (h-layer) improves the selectivity to textural elements on the basis of their size. In each layer, cells have RFs selective to oriented features and are arranged in a topographic map; in the drawings cortical cells are represented by the orientation to which they are selective. Cells belonging to the same hypercolumn have RFs that overlap almost completely , while cells belonging to adjacent hypercolumns have RFs that overlap only partially as illustrated in (*b*). In the main diagram (*a*), the three layers and the flow of information among them are evidenced. Black arrows indicate inhibitory connections, while white arrows indicate excitatory connections. The shaded-bordered rectangles, coded by FU, FCOI, and CFL, represent the type of processing occurring in the point of the network to which they are referred. In the insets (from (*d*) to (*f*) are evidenced the topological pattern of connections between layers. The marked cell receives input from the cells located in the shaded areas and the color of the afferent cell codes the type of contribute: positive if the cell is white, negative if the cell is black *d*. Both ON and OFF type cells, as well as even and odd receptive fields are presented. The set of the four cells with the same orientation preference (ON, OFF, even, odd) may be defined as a *functional unit* (FU). In the c-layer, cells receiving input from the corresponding functional unit, result to be selective to oriented features independently of their contrast and their phase. The lateral inhibition schema depicted in (*c*) is the *functional cross-orientation inhibition* (FCOI): a target cell with orientation preference θ receives inhibitory input from two complex cells, selective to $\theta + 90^{\circ}$, belonging to hypercolumns that lay along an axis orthogonal to θ. This inhibition process is present both in c-layer and h-layer. The *cooperative feedback loop* (CFL) is the type of process present between c-layer and h-layer: an hypercomplex cell selective to θ receives an excitatory input from the complex cells, having the same orientation selectivity, and belonging to neighboring hypercolumns (*e*); the same hypercomplex cell sends an excitatory feedback to the corresponding cell on the c-layer.

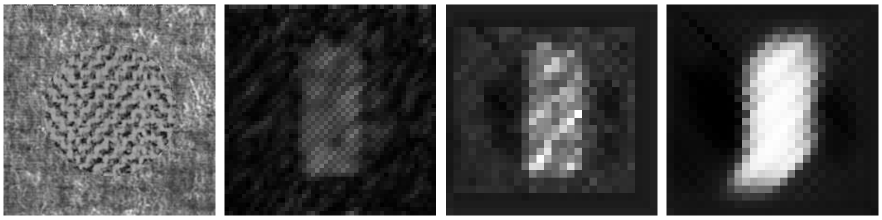

Figure 3: From left to right: the test image, the output of the simple cell layer, the output of the complex cell layer and the output of the hypercomplex cell layer. It is worthy to note that the level of segregation increases with the layer