Cortical Perceptual Processing Mapped into an Active Resistor Network

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Abstract

Recently an isotropic resistive network that performs a Gaussian filtering of an image for pre-processing tasks in image analysis has been proposed. In this paper, starting from biological considerations on cortical organization, we propose an anisotropic resistive network able to extract local features of an image, that can be used to detect variations of texture and to perform higher level visual tasks.

1 Introduction

A great deal of visual tasks is solved by animals and humans in a preattentive phase, without focusing of attention. In this phase, vast arrays of intercommunicating, identical processes carry out low-level vision tasks such as perceiving edges by texture differences, depth mapping, computing optical flow, recovering local surface structure, segmenting images, etc. To extract information relevant to movement or action (e.g. of a robot) it is fundamental that such low-level processes can be performed in real time. Thus, analog hardware devices, with embedded image sensing, are of great interest in machine vision. In such devices, information, indeed, is really distributed, being mapped directly in the electrical variables, and computation is carried out massively in parallel with high efficiency and speed. In the perceptual phase, the brain analyzes the scene and extracts symbolic information to form an abstract representation of the external environment [1]. Hence, the tasks involved in this phase are 1) to map from the original pattern of light intensities to intermediate abstract representation by means of appropriate receptive fields and 2) to arrange information in functional mapping apt to help all subsequent processes to come up with useful image descriptors.

In this paper we present an active resistor network in which different orientation-selective neurons, are simultaneously realized on the same layer, according to a simulated orientation domain of the mammalian visual cortex. Each neuron (or node) has a receptive field that is characterized by an elongated two-dimensional Gabor-like profile. Network performance is evaluated to test its potential use in compact machine-vision systems.

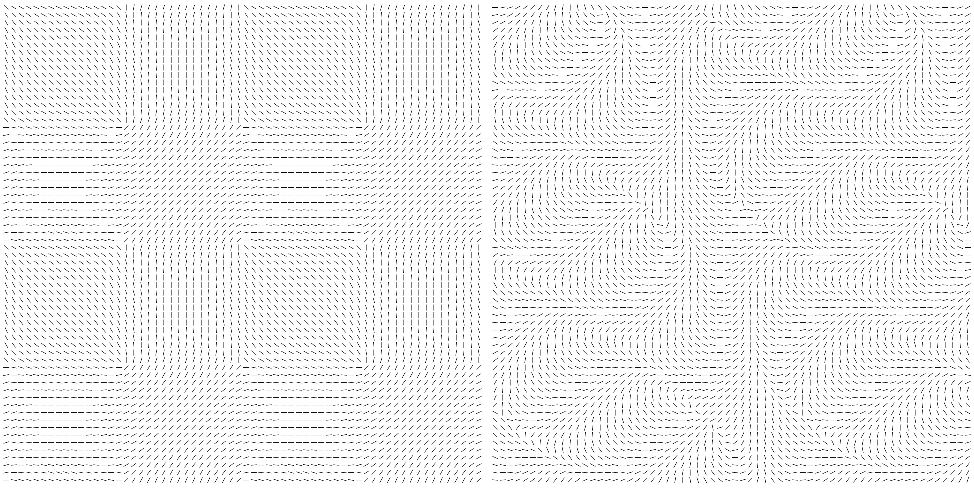
2 Neurophysiological basis for complex stimulus perception

Computational solutions evolved by nature, are particularly valuable in designing neural devices for optimal feature extraction, and neuromorphic architectures to solve perceptual tasks.

At first stages of perception, retinal ganglion cells provide local contrast information to higher stages. Combining such information, receptive fields of striate cortex become complex enough to handle symbolic information. In the striate cortex a wide class of cortical cells are characterized by elongated receptive fields with parallel subregions alternately driven by stimuli of opposite contrast, that can be closely fitted by two-dimensional Gabor functions. The properties of these functions in maximizing the joint selectivity in space and frequency domain, and their efficacy in optimal image filtering have been widely investigated [4][9].

The characteristics of such operators guarantee the extraction of information on both the orientation and the spatial frequency of the local visual stimulus and allow a multi-channel approach for image analysis. However, to solve simple visual tasks, we need blending information from different channels [5]. More specifically, a simultaneous analysis of small areas of the image by multiple differently oriented filters, compatibly with the sensor resolution, and functional interactions among them, are required to enhance their selectivity to orientation contrast. To fulfill these demands, the mammalian visual system resorts to two computational principles, embodied in its structure. First, the existence of a retinotopic mapping preserves topological relations of the input images so that two nearby points in the retinal image activate nearby points on the cortical surface. Second, orientation-selective neurons are horizontally arranged in an ordered fashion (orientation map) to help cooperation and competition among different orientations with minimal wiring demand.

The organization of the orientation-selective cells in the visual cortex fulfills two golden rules: (1) all orientations are well-represented in a small area, (2) in a more restricted area neurons have similar orientation preference. Several models, driven by functional considerations [2] or mathematical description of real orientation maps [10], have been presented and simultaneously, experimental research provided new insights on the organization of the orientation maps. Two examples of biological-plausible maps are depicted in Fig.1.



(a) (b)

Figure 1: Examples of biological plausible orientation maps: (a) a plaid-like map and (b) a more realistic one.

3 The Architecture of the Resistive Network

The starting point is the schema shown in Fig. 2 for an isotropic square grid network: g_1 is the conductance value of positive interconnected resistors; $g_2 = -g_1/4$ is the value of negative resistors, and g_0 is the value of node-to-ground resistors. The 2D distribution of the current sources represents the input image. The output image is represented as the node voltage distribution of the array. The steady-state signal processing functionality of the network is completely described by the shape of the node voltage response to a constant current excitation at a single node. For the mesh in Fig. 2, such a response is similar to a Gaussian function centered around in the excited node; the width of the Gaussian function depends on the (g_1/g_0) ratio.

To generate elongated Gaussian functions, we consider an extra positive resistor of conductance G from the node, in the direction of the orientation selectivity we need [7].

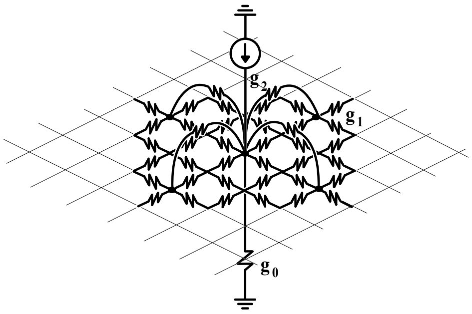
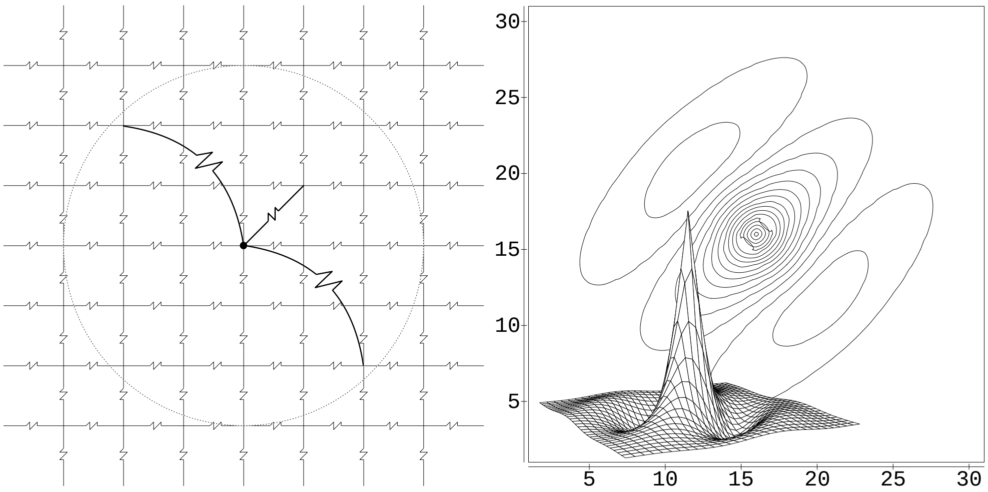


Figure 2: The basic schema of the connections from a node: an input current proportional to the luminous intensity is provided by a photoreceptor, that is here represented by a generator.

To improve the spatial frequency selectivity, a Gabor-like convolution kernel should be used. Following the approach described [7], we add two negative resistors for each node, arranged in the direction orthogonal to the one to which the node is selective and at a distance related to the width of the modulating Gaussian function (see Fig. 3a for the case $\pi/4$ and inhibition radius 3). In Fig. ??b, a Gabor-like operator with the orientation preference $\pi/4$ is depicted: it has been obtained by a 31×31 grid, and by inhibition radius 6.



(a) (b)

Figure 3: (a)Connections to obtain a Gabor-like operator oriented along $\pi/4$ with inhibition radius 3. (b) Perspective and contour plots for the Gabor-like operator oriented along $\pi/4$ with radius 6 for a 31×31 node.

This result can be extended to the implementation of orientation maps by varying the pattern of interconnections of the resistor mesh in a continuous fashion [8].

Among all the biological plausible orientation maps that are in accordance with the above-mentioned golden rules, we will refer here to the two shown in Fig. 1 which allow us to have uniform areas, large enough to obtain well shaped and well-oriented convolution kernels. The minimal portion of the array containing nodes selective to all the orientations present in the map will be refered in the following as the basic *module* of the map.

4 Experimental results

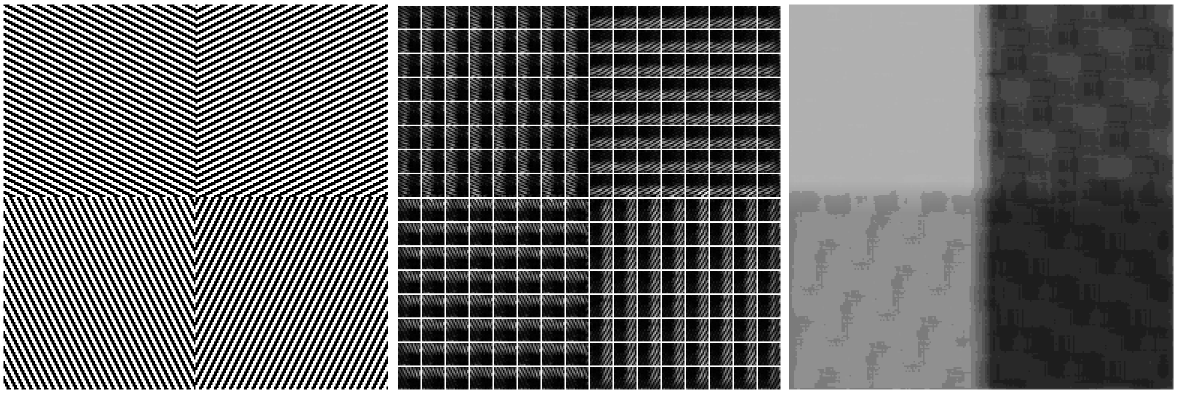
Our network is able to detect texture differences in an image by different responses of cells selective to different orientations, as other networks based on biological considerations do [9][3]. Indeed, if the test image is composed of repeated oriented elements, the cells in the regions of the map selective to that orientation have the strongest output.

For testing network performances we have considered at first a synthetic image containing four different oriented textures (see Fig. 4a. In Fig. 4b the output of the network that implements the cortical map on the left shown in Fig. 1a is depicted subdivided in domains (collecting all considered orientations). Ignoring the border effect, we can note that regions with uniform texture lead neurons to have similar domain responses. More generally different texture structures correspond to different patterns of excitation on the cortical map. The output of the orientation map can be used as the basis for a post-processing phase to provide a texture classification. This is not sufficient on its own to solve segmentation processes and an efficient strategy to bind features must be introduced.

There is a strong evidence that in real visual cortex, the average characteristics of local-field potentials may aggregate local information of small assemblies of neurons selective to a complete set of orientations. The spatio-temporal characteristics of such local-field potentials yield global perception about edges separating one region from another and determine regions on the basis of continuity of structure.

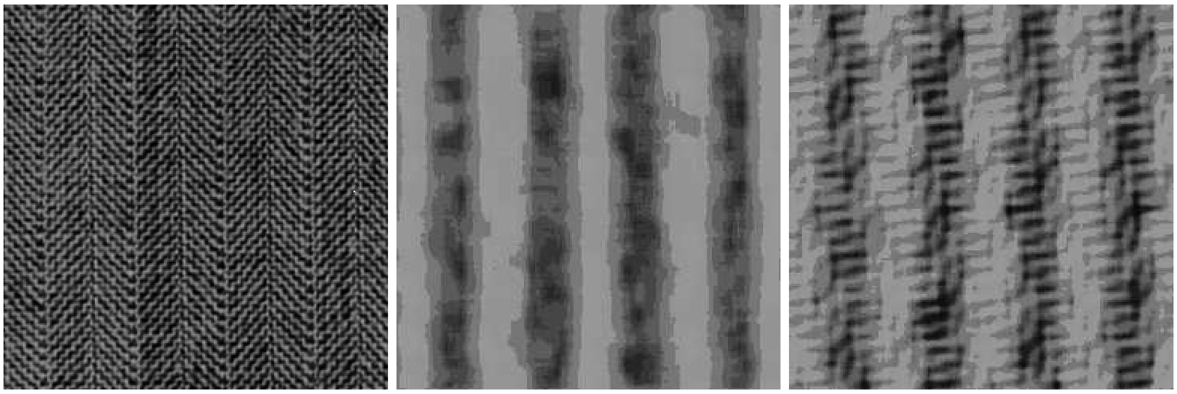
The development of a suitable algorithm to solve on the same devices the binding problem will be argument of a future work. However, to show that global coding is conceptually feasible, we made an effective color display of texture information assigning different colors to different orientations and modulating the luminous intensity according to the activity of the neurons. In order to consider a global coding the color-merging is simulated with an average operation. The value of each component is obtained by averaging the output over an array portion centered in the node of the same size as the map's module.

Under this assumptions it is possible to discriminate a number of textures equal to all the nuances of the color palette. In the last image of Fig. 4c the result of this operation subjected to the constraints of the gray-level representation is shown. Network performances on natural texture image (Fig. refnata) have been evaluated and the results obtained with the two maps in Fig. 1 are shown in Fig. 5bc.



(a) (b) (c)

Figure 4: (a) the synthetic textured pattern image, (b) the output of the network subdivided into orientation domains, (c) the global coding of textural information (see text).



(a) (b) (c)

Figure 5: From left to right: a natural textural image and the segmentated images for the cortical maps of Fig. 1.

5 Discussion and Conclusions

The active resistor network presented in this paper, provides an efficient hardware solution to real-time low-level visual tasks. The topology of the network allows, indeed, an efficient feature extraction and image representation, but should also provide an effective solution for subsequent local symbolic interactions, particularly useful for texture segregation.

Moreover, we have shown how complex operators for low-level image processing can be mapped, with low effort, directly in the structure of a resistor network. Such network reveals itself particularly robust, indeed, the choice of the value of the resistances is not critical since the final orientation of the convolution kernels is more a consequence of the topology of connections than of a proper choice of these values.

Concerning the implementability on VLSI hardware of this network, we have to express it in terms of a set of computational primitives, representing the resources available for the realization of the system, and of the rules that determine the interactions among the blocks implementing those primitives. While in a digital system the primitives are simple logical operators (AND, OR, NOT, ...), in analog neural system the functionalities of the primitives present higher complexity, even if the rules are represented by Kirchoff's laws. In particular, in the network here presented, we can identify three basic primitives: resistors, active resistors and photoreceptors.

Various choices are available to the circuit designer for the implementation of such primitives: fixed resistors can be implemented in silicon with paths of diffusions with assigned resistivity; properly biased MOS transistors can act as variable resistors; active resistors can be implemented by more complex circuitry, such as operational amplifiers or negative impedance converters; finally, photoreceptors can be implemented through p-n junctions (photodiodes or phototransistors), being its reverse current proportional to the incident light intensity. The previous choices determine the number of nodes (i.e. pixels) the network is able to process. By example, in [6] on a silicon area of $8mm \times 9mm$ using a $2\mu m$ CMOS technology and phototransistors that take up a $26\mu m \times 54\mu m$ silicon area, an exagonal grid of simmetrical gaussian operators 45×40 is proposed. In such implementation the dimensions of the operators are controlled by a variable resistor (g_0), which is responsible of the 75% of the power dissipation.

The network we propose considers additional resistors to implement Gabor-like oriented receptive-fields for higher level processing; though we disregard the variability of the resistors in order to dissipate less power and increase operator density. It is not so easy (or, at least, not possible on a cost basis) to meet constraints on power dissipation and area occupation, with present commercially available technologies, for a network of 256×256 nodes, however the design of a smaller network is under development.

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