Comunicazione orale

Spatio-Temporal Image Operators Based on Asymmetric Interaction Schemes

Operatori Spazio-Temporali di Immagini Basati su Schemi di Interazione Asimmetrici

Fabio Solari
Dipartimento di Ingegneria Biofisica e Elettronica
Università di Genova-Via all'Opera Pia 11/A-16145 Genova-ITALY
fabio@dibe.unige.it

1 Introduction

Information on the direction of motion can be related to filtering operations on the image sequence with localized kernels oriented in space-time. Such operators emulate the functionality of a large class of cortical neurons (simple cells) observed in the visual cortex. Simple cells have indeed a very specific space-time behavior in which the spatial phase of the receptive field changes gradually as a function of time [3]. This results in receptive field profiles that are tilted along an oblique axis in the space-time domain (i.e, space-time inseparable).

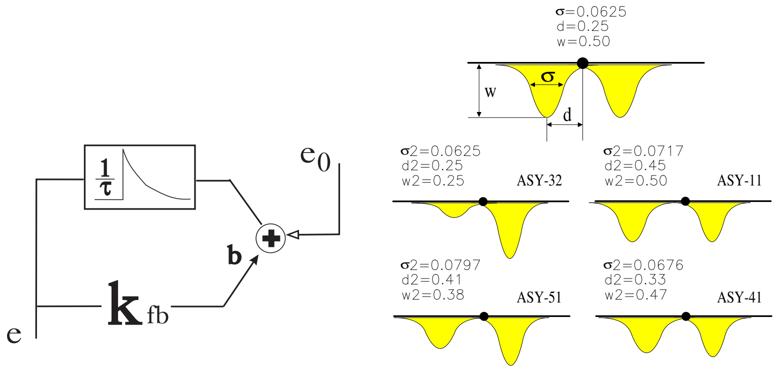
In this paper, within a linear field theory framework, we propose and analyze an architectural model for dynamic receptive field formation, based on intracortical interactions occurring through asymmetric recurrent inhibition schemes. Asymmetries are analyzed under different facets in relation to a basic arrangement of inhibitory interconnections characterized by a symmetrical spatial structure. Changing type and degree of asymmetry, different types of direction selectivities arise, as they are observed in the visual cortex.

2 The Cortical Network

Following a linear neural field approach, we regard visual cortex as a continuous 2-D distribution of neurons and synapses. This network layer models neuron population: each point in space $[\mathbf{x} = (x, y)]$ corresponds to an "average neuron". The spatial coupling of these populations is described continuously by space-invariant[1] 2-D kernels on the plane, which represent the functional spread of the synaptic influence of a population on its neighbors, as mediated by local axonal and dendritic fields.

An architectural diagram of the cortical network is drawn in Fig. **??** a). The dynamics of the layer is modeled as a 1st-order low-pass filter,

[1] A space-variant extension of the model evades the scope of this work, and, limited to the steady-state condition, can be found elsewhere [4].



a) b)

Figure 1: a) Block diagram representation of Eq (**??**): the system is a first-order recurrent loop with time constant τ, ignited by LGN afferents (e_0).(b) The basic (symmetric) inhibitory kernel $k_{FB}(x-\xi)$ (top). The cell in the centre receives inhibitory contributions from laterally distributed clusters of cells. The asymmetric kernels represented derive from this basic kernel by systematic variations of its geometrical parameters.

characterized by a time constant τ. The processing is due to recurrent interactions among populations.

The excitation $e(\mathbf{x},t)$ can be obtained as the solution of a single-layer linear field equation of lateral inhibition type [1]:

$$\tau\frac{\mathrm{d}e(\mathbf{x},t)}{\mathrm{d}t} = -e(\mathbf{x},t) + e_0(\xi,t) + b\int k_{fb}(\mathbf{x}-\xi)e(\xi,t) + \mathrm{d}\xi \tag{1}$$

where b is the interaction strength, and $k_{fb}(\mathbf{x}-\xi)$ is the feedback interaction kernel. The geniculate contributions $e_0(\xi,t)$ can be modeled directly as spatiotemporal convolutions on the visual input $s(\mathbf{x},t)$ through separable kernels $h_0(\mathbf{x},t) = f_0(\mathbf{x})g_0(t)$, characterized in the spatial domain by Gaussian shapes with an extent σ_0, and, in the temporal domain, by a 2nd-order impulse response: $g_0(t) = \exp(-t/\tau_0)\sin(\omega_s t)$ with a damping ratio $1/\sqrt{(\tau_0\omega_s)^2+1}$ fixed to 0.3.

The inhibitory kernel k_{FB} is modeled [4] as the sum of two Gaussians, symmetrically offset with respect to the target cell (see Fig. **??**b):

$$k_{fb}(x) = \frac{1}{2\pi}\left(\frac{w_1}{\sigma_1^2}\exp[-(x-d_1)^2/2\sigma_1^2] + \frac{w_2}{\sigma_2^2}\exp[-(x+d_2)^2/2\sigma_2^2]\right). \tag{2}$$

3 Emergence of direction selectivity

We can solve the integro-differential equation (**??**) in the Fourier domain: $E(\mathbf{u},\omega) = H(\mathbf{u},\omega)S(\mathbf{u},\omega)$ with

$$H(\mathbf{u},\omega) = H_0/(1 + j\omega\tau - bK_{FB}(\mathbf{u})) \tag{3}$$

where $\mathbf{u} = (u, v)$ and ω represent the spatial and temporal frequencies, respectively, and the upper case letters refer to Fourier transforms. For the sake of simplicity, in the following we restrict the spatial analysis to 1-D case, *along the direction orthogonal to the preferred orientation of the receptive field.* To better evidence feedback contributions in the activity, it is convenient to rewrite Eqs. (**??**) as

$$H(u,\omega) = \frac{1}{1 + j\omega\tau} H_0(u,\omega)[1 + bK_{FF}(u,\omega)] \tag{4}$$

where

$$K_{FF}(u,\omega) = K_{FB}(u)/(1 + j\omega\tau - bK_{FB}(u)) \tag{5}$$

is the *equivalent feed-forward kernel* of the recurrent loop, that summarizes all the effects of feedback. $K_{FF}(u,\omega)$ interacts with the initial filter $H_0(u,\omega)$ molding its energy distribution in the resulting filter $H(u,\omega)$.

The shape of the interaction kernel K_{FB} determines the effectiveness of the recurrent network in generating the properties of the modeled cortical neurons. Asymmetrical profiles of $k_{FB}(x - \xi)$ give rise to complex forms of $K_{FB}(u) = \mathrm{Re}\{K_{FB}(u)\} + j\mathrm{Im}\{K_{FB}(u)\}$ in Eq. (**??**) and hence to complex poles that result in spatio-temporal oscillatory behaviors. This becomes more apparent if we rewrite K_{FF} as:

$$K_{FF}(u,\omega) = \underbrace{\frac{K_{FB}(u)}{1 - b\mathrm{Re}\{K_{FB}(u)\}}}_{spatial\ term} \underbrace{\frac{1}{1 + j\tau_{eff}[\omega - \gamma(u)]}}_{spatio-temporal\ term} \tag{6}$$

where $\tau_{eff} = \tau_{eff}(u) = \tau_1/(1 - b\mathrm{Re}\{K_{FB}(u)\})$ is the effective time constant of the system resulting from the recurrence loop, and $\gamma(u) = \mathrm{Im}\{K_{FB}\}/\tau_1$ is the value of the temporal frequency shift of the amplitude energy spectrum.

The real part of the recurrent kernel is the major responsible of the low-pass to band-pass transition in the spatial domain, whereas the shift of the spectrum in the spatio-temporal frequency domain depends exclusively on its imaginary part.

We chose four coupling kernels represented in Fig. **??** b). They can be considered as representative of different kind of asymmetries. As expected, increasing the parameter b enhances the effects of inhibition, thus resulting in larger direction selectivity. The asymmetries in the spatial offset of the cortical inhibitory sites reveal to be the most effective to induce high direction selectivity as it could be inferred also from the spatio-temporal receptive fields which present a marked motion-type (i.e., oriented) non-separability (see Fig. **??** (top)).

4 Discussion

In this paper, we demonstrated that a purely spatial asymmetry is sufficient to generate directional selectivity, when spatially asymmetric contributions

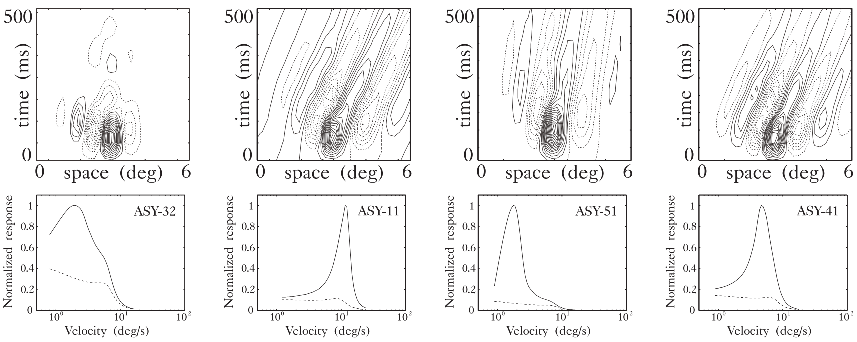


Figure 2: Results from the model for each asymemetry considered. (Top) Spatio-temporal contour plots represent the resulting receptive fields for $\tau_0 = 20$ms. Continuous lines indicate excitatory subregions, whereas dashed lines indicate inhibitory subregions. The RF are tilted towards the side where the inhibitory couplings are most effective (i.e., strongest or nearest). (Bottom) Velocity tuning curves of the resulting receptive fields. Continuous lines represent the responses in the preferred directions, whereas dashed lines are the responses in the non-preferred directions.

arise through recurrent intracortical inhibitory circuits. The space-time asymmetry of the resulting receptive field emerges as a *dynamic property* of the cortical network, thus leading to highly structured space-time receptive fields from space-time separable Gaussian subunits (i.e., geniculate inputs).

These results can guide the implementation, through circuital lattice networks [2], of spatio-temporal image operators capable discriminating motion

Acknowledgments The author wishes to thank G.M. Bisio and S.P. Sabatini for useful suggestions.

REFERENCES

1. S. Amari, Dynamics of Pattern Formation in Lateral-inhibition Type Neural Fields, Biol. Cybern., vol. 27,1977, 77–87.

2. G.M. Bisio and L. Raffo and S.P. Sabatini, Analog VLSI Primitives for Perceptual Tasks in Machine Vision Neural Computing and Application, 1998.

3. D.B. Hamilton and D.G. Albrecht and W.S. Geisler, Visual cortical receptive fields in monkey and cat: spatial and temporal phase transfer function, Vision Res., vol 29(10), 1989, 1285–1308.

4. S.P. Sabatini, Recurrent inhibition and clustered connectivity as a basis for a Gabor-like receptive fields in the visual cortex, Biol. Cybern., vol. 74(3), 1996, 189–202.