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Mediated by
Self-Organized Lateral Connections

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November 1999 AI TR99-283
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November 9, 1999

Abstract
Contour integration is believed to occur based on lateral interaction between neurons with similar orientation tuning. The exact neural mechanisms underlying such interactions, and their developmental origins, are not well understood. This paper suggests through computational simulations that synchronization mediated by patchy lateral connections, formed through input-driven self-organization, can serve as such a mechanism. Furthermore, such patchy connections may explain why different areas of the visual field show different degrees of contour integration in psychophysical experiments.

1 Introduction
Contour integration means forming a single coherent percept (i.e. a continuous contour) from a discontinuous sequence of line segments. Psychophysical experiments (Field et al. 1993; Pettet et al. 1998) and computational models (Yen and Finkel 1997; Li 1998; Yen and Finkel 1999) suggest that contour integration in the visual cortex may be due to interaction of neurons with similar orientation tuning. The models perform integration based on predetermined set of constraints such as relative orientation difference, distance, curvature, and change in curvature, and they match experimental data quite well. However, how such constraints are implemented in the brain and how they emerge during early life of the animal is an open question at this point. Furthermore, the models do not explain why contour linking is absent in the peripheral vision (Hess and Dakin 1997), and why subjective contours are harder to perceive in the upper vs. the lower hemifield (Rubin et al. 1996).

This paper explores the possibility that a single mechanism of synchronization mediated by self-organized lateral connections may be responsible for these phenomena. Previous computational studies on cortical self-organization have shown that strong lateral connections develop between neurons with similar orientation preference, and these connections can serve as a foundation for segmentation and binding (RF-SLISSOM, or Receptive Field Spiking Laterally Interconnected Synergetically Self-Organizing Map; Choe and Miikkulainen 1998; Sirosh 1995; Sirosh et al. 1996; Miikkulainen et al. 1997). This paper shows that (1) such lateral connections can also establish contour integration, (2) the specific lateral connection patterns necessary for contour integration can be learned in an input-driven self-organizing process like the rest of the orientation map, and (3) the weaker integration in peripheral vs. foveal and upper vs. lower hemifield may result from weaker lateral connectivity patterns, which in turn may originate from attentional modulation of the frequency and quality of input (Previc 1990). At first, however, the present RF-SLISSOM model must be extended to include long-range excitatory lateral connections.
2 Extending RF-SLISSOM to Contour Integration

The contour integration model is based on the RF-SLISSOM model of self-organization and segmentation in the visual cortex. In RF-SLISSOM, each cortical neuron receives afferent connections from the input layer and lateral (excitatory and inhibitory) connections from other neurons in the cortex. The connection strengths are self-organized based on correlations in the input. In the final ordered map, the lateral excitation has a short range, and causes neurons responding to the same input object to fire synchronously, thereby binding the representation into a single coherent percept. The lateral inhibitory connections have a long range, and establish competition between representations of different objects. Neurons representing different objects tend to fire at different times, and the input is thereby segmented into different objects.

The RF-SLISSOM model shows how self-organization and segmentation can be achieved in a single unified model. The long-range lateral interactions play a crucial role in both behaviors: they establish competition that drives self-organization, and they establish desynchronization that drives segmentation. The model does not include any long-range excitatory connections because they were not found necessary to model the above behaviors.

However, it turns out that such a parsimonious model cannot account for filling-in phenomena such as contour integration. The network has to be able to bind together representations that are separated by gaps: that is, it has to have long-range excitatory connections that link together the representations of the different segments of a fragmented contour.

The RF-SLISSOM model is extended in this paper with such long-range excitatory connections (figure 1). For conceptual clarity, the cortical network is divided into two separate components: (1) MAP1, which is similar to the RF-SLISSOM cortex with short-range excitatory and long-range inhibitory connections. This map has the task of driving the self-organization of the network into an ordered map. (2) MAP2, which has the task of establishing long-range segmentation and binding, with long-range excitatory connections that allow contour integration, and long-range inhibitory connections that allow segmentation of separate objects.

The two maps are assumed to be overlaid in one cortical network. In other words, the model predicts that some of the neurons in each hypercolumn are involved in establishing and maintaining organization, whereas others perform visual segmentation and binding. The details of the architecture, referred to as Stacked RF-SLISSOM, are described next.

3 The Network Architecture

The details of the neuron model are shown in figure 1a. Each connection is a leaky integrator that performs exponentially decayed summation of incoming spikes, thereby establishing not only spatial summation, but also temporal summation of activity. The spike generator compares the net input to a threshold and decides whether to fire a spike. The threshold is a sum of two factors: the base threshold $\theta$ and an exponentially decayed sum of past spikes, formed by a similar leaky integrator as in the input synapses (Eckhorn et al. 1990; Reitboeck et al. 1993).

The overall organization of the Stacked RF-SLISSOM model is shown in figure 1b. The net input $\sigma_{ij}(t)$ to the spike generator of the cortical neuron (in each map) at location $(i, j)$ at time $t$ consists of the input from a fixed-size receptive field in the retina, centered at the location corresponding to the neuron’s location in the cortical network, from neurons around the same location in the other map, and from neurons around it in the same map:

$$
\sigma_{ij}(t) = \gamma_a \sum_{r_1, r_2} \xi_{r_1, r_2} \mu_{ij, r_1, r_2} + \gamma_c \sum_{p_1, p_2} \zeta_{ij, p_1, p_2} \nu_{ij, p_1, p_2}
+ \gamma_e \sum_{k, l} \eta_{kl} (t-1) E_{ij, kl} - \gamma_i \sum_{k, l} \eta_{kl} (t-1) I_{ij, kl},
$$

(1)

where $\gamma_a$, $\gamma_c$, $\gamma_e$, and $\gamma_i$ are the relative strengths of the afferent, intra-columnar, excitatory, and inhibitory contributions, $\xi_{r_1, r_2}$ is the decayed sum of spikes of the retinal neuron $(r_1, r_2)$, $\mu_{ij, r_1, r_2}$ is the corresponding afferent connection weight, $\zeta_{ij, p_1, p_2}$ is the decayed sum of spikes of the cortical neuron $(p_1, p_2)$ of the other cortical map, $\nu_{ij, p_1, p_2}$ is the corresponding intra-columnar connection weight, $\eta_{kl} (t-1)$ is the decayed sum of spikes from the map neuron $(k, l)$ at time $t-1$, and $E_{ij, kl}$ is the corresponding excitatory and $I_{ij, kl}$ the inhibitory lateral connection weight.
The input is kept constant while the cortical response settles through the lateral connections, forming a concentrated, redundancy-reduced activation pattern. The retinal neurons are spiking constantly at each iteration and the cortical neurons are allowed to exchange spikes. After a while, the neurons reach a stable rate of firing, and this rate is used to modify the weights. The afferent, lateral and intra-columnar weights are modified according to the Hebbian principle:

\[ w_{ij,mn}(t) = \frac{w_{ij,mn}(t-1) + \alpha V_{ij} X_{mn}}{\sum_{mn} [w_{ij,mn}(t-1) + \alpha V_{ij} X_{mn}]} \]

where \( w_{ij,mn}(t) \) is the connection weight between neurons \((i, j)\) and \((m, n)\), \( w_{ij,mn}(t-1) \) is the previous weight, \( \alpha \) is the learning rate (\( \alpha_a \) for afferent, \( \alpha_c \) for intra-columnar, \( \alpha_e \) for excitatory, and \( \alpha_i \) for inhibitory connections), \( V_{ij} \) and \( X_{mn} \) are the average spiking rates of the neurons. Those connections that become zero in this process are killed, modeling death of unused connections.

This process of weight adaptation is repeated for a number of input patterns (e.g. oriented Gaussians), and the neurons become gradually sensitive to particular orientations at particular locations, and the map forms a global retinotopic orientation map similar to that in the visual cortex (Blasdel 1992; Blasdel and Salama 1986). The self-organized map will then synchronize and desynchronize the firing of neurons to indicate binding and segmentation of visual input to different objects.

### 4 Experiments

A Stacked RF-SLISSOM network with a \( 36 \times 36 \) retina and a \( 48 \times 48 \) cortex was trained for 20000 iterations with elongated Gaussian bars at random locations in the retina. Excitatory lateral connections in MAP1 had an initial radius of 3 and gradually reduced to 1, and inhibitory lateral connections had a fixed radius of 10. In MAP2, both types of lateral connections had a radius of 19. Afferent connections to the retina had a radius of 7 in both maps, and intracolumnar connections a radius of 1. During each training presentation, the network was allowed to settle for 13 time steps (through equation 1) and all connections except MAP2 inhibition were updated according to equation 2. The fixed MAP2 inhibition provides a baseline global inhibition similar to many other cortical models (Eckhorn et al. 1988; von der Malsburg and Buhmann 1992), which is simple and sufficient to establish segmentation. The simulations are not particularly sensitive to these parameter values as long as they have said qualitative properties.

A well-formed orientation map emerged in this process in 20000 iterations (figure 2a). The lateral connections with weights less than 0.001 were killed in the end, thus leaving a patchy connection profile (figure 2b).