Perceptual Grouping in a Self-Organizing Map of Spiking Neurons

Yoonsuck Choe
Department of Computer Sciences
The University of Texas at Austin

August 13, 2001
Perceptual Grouping

Group Two! Longest Contour? What is in here?

Goal: To understand the Neural Mechanisms of Perceptual Grouping.
Perceptual Grouping

- How are constituents grouped together?
- The neural mechanisms are not well understood.
- As a first step, focus on the **Low-Level**.
Low-Level Perceptual Grouping

Why focus on low-level?

- Constraints on feature dimensions.
- Abundant neuroanatomical data.
- Bridge to high-level cognitive processes.
- Example: **Contour Integration**
Research Questions

1. What are the neural mechanisms?

2. How does the circuitry emerge?
1. **Synchronized activity** represents grouping.

2. Circuitry is **self-organized** during development.
   (Unsupervised learning)
Basics(1): Human Visual Pathway

- Receptive Fields ($RF$).
- Hierarchy of maps.
  1. Topological organization.
  2. Laterally connected.
Basics(2): Primary Visual Cortex

- Neurons are orientation-tuned.
- Nearby neurons prefer similar orientation.
- Forms orientation map.
Basics(3): Lateral Connections

Bosking et al. (1997)

- Black dots: Lateral Connections.

- Connect similarly orientation-tuned neurons.

(Gilbert and Wiesel, 1989)
Synchronization

Eckhorn et al. (1988); Gray et al. (1989)
Contour Association Field

D. Field et al. (1993)

- Smaller relative orientation is preferred.
- Edges *aligned on a common path* are preferred.
- Conjecture: *lateral interaction* is needed.
Local Grouping Function

Geisler et al. (2001)

- Edge co-occurrence in natural images
  → Local grouping function.

- Transitive grouping rule.

Predict human contour integration performance.
Self-Organization

Altered visual environment drastically changes the organization of the visual cortex.

- **Input deprivation:** Hubel and Wiesel (1962, 1974), Issa (1999), White et al. (2000, 2001)

- **Biased input:** Hirsch and Spinelli (1970), Blakemore and van Sluyters (1975)

- **Visual input to auditory cortex:** Sur et al. (1988), Sharma et al. (2000)
## Computational Models

<table>
<thead>
<tr>
<th>1. Synchronization</th>
<th>2. Self-Organization</th>
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</table>
| ● Coupled Oscillators  
von der Malsburg & Buhmann (1992)  
Chakravarthy, Ramamurti & Ghosh (1995)  
● Leaky integrator  
Eckhorn et al. (1990)  
Reitboeck et al. (1993)  
● Integrate and fire neurons  
Nischwitz and Glünder (1995) | ● Orientation map  
von der Malsburg (1973)  
Obermayer et al. (1990)  
● Ocular dominance  
Miller et al. (1989)  
● LISSOM: SOM with lateral conn.  
Miikkulainen, Bednar, Choe & Siros (1997) |

### 3. Contour Integration

- ● Fixed, pre-calculated lateral interaction patterns.  
  Li (1998), Yen and Finkel (1997)
Limitations

1. Lack temporal representation.

2. Limited to simple grouping rules such as connectedness.

3. Fixed lateral interaction:
   - No self-organization.
   - Does not explain how such patterns emerge.
   - Does not explain hemifield differences in performance.
Integration of two computational principles:

1. **Temporal Coding**
   - Spiking neurons.

2. **Self-Organization**
   - Oriented RFs and patterned lateral connections.
Architecture: PGLISSOM

1. Spiking Neurons.

2. Afferent connections form oriented RF.

3. Excitatory and inhibitory lateral connections.

4. Two layers, constituting a cortical sheet.
   - Self-Organization
   - Grouping
Spiking Neuron

- Leaky Synapse

\[ s(t) = i + s(t - 1)e^{-\lambda} \]

- Dynamic Threshold (Refractory Period Term)

\[ \theta(t) = \theta_{\text{base}} + \tau \theta_{\text{rel}}(t) + \theta_{\text{abs}}(t) \]
\[
\sigma_i = g \left( \gamma_a \sum_j \mu_{ij} \xi_j + \gamma_c \sum_k \nu_{ik} \zeta_k + \gamma_e \sum_m E_{im} \eta_m - \gamma_i \sum_m I_{im} \eta_m \right)
\]

- **Afferent**
- **Intra-Column**
- **Exc.Lat.**
- **Inh.Lat.**
Weight Adaptation

Normalized Hebbian Learning:

\[ w_{ij}(t + 1) = \frac{w_{ij}(t) + \alpha V_i X_j}{\sum_j [w_{ij}(t) + \alpha V_i X_j]} \]

- Increase weight proportional to the activities.
- Normalize with sum of weights to limit growth.
Summary of Results

1. Self-organized orientation map.
2. Self-organized lateral connections.
3. Lateral connection statistics.
5. Contour segmentation.
6. Contour completion.
7. Hemifield differences in contour integration.
Results(1): Orientation Map

- Trained with elongated, oriented Gaussians as input.
- Activate, settle, and adapt weights.
- Smooth orientation map develops in both layers.
Results(2): Lateral Connections

- MAP2 excitatory connections are shown.
- Connects similarly orientation-tuned neurons.
- Aligned along the axis of the source neuron’s RF.
- Synchronizes remote areas.
Results(3): Connection Statistics (I)

- Connections prefer similar orientation.
- Matches data from Bosking et al. (1997).

Bosking (1997)
Results(3): Connection Statistics (II)

- Connected RFs are aligned along a smooth path.
- Matches edge co-occurrence statistics found in nature.
Connection Statistics(II): Zoomed

\[ \phi = 90^\circ \]

Relative Probability

\begin{align*}
\delta &= 27 \\
\phi &= 90^\circ
\end{align*}

Likelihood Ratio

\begin{align*}
\delta &= 1.23^\circ
\end{align*}
Why Co-Circular?

- RFs aligned on a common straight input are stimulated.
- Non-optimally aligned input can also cause activity.
- Forms the basis for contour integration.
Results(4): Contour Integration

- Performance measure:
  Correl. coeff. between Multi Unit Activities (MUAs).
- As orientation jitter increases:
  - correlation decreases (PGLISSOM).
  - accuracy decreases in humans (Geisler et al. 2001).
Demo

Contour Integration
Results(5): Contour Segmentation

- Each contour is grouped by synchronized activity.
- Separate contours are segmented by desynchronized activity.
Demo

Contour Segmentation
Results(6): Contour Completion (I)

- Illusory contours: Kanizsa square.
- Edge-inducers around the border.
- Contour completion may be a low-level mechanism.
Demo

Contour Completion
Results (6): Contour Completion (II)

- Gap region receives small amount of afferent input.
- However, completion is not due to afferent input alone.
- Completion is not due to excitatory input alone either.
Contour and illusory contour detection performance differ:

- Fovea $> \text{Periphery}$ (Hess and Dakin 1997)
- Lower $> \text{Upper Visual Hemifield}$ (Rubin et al. 1996)
Results(7): Hemifield Differences(I)

- Input **presentation frequency** differed in the hemifields.

- Resulting excitatory lateral connections are:
  1. more **co-circular** in the lower hemifield, and
  2. more **collinear** in the upper hemifield.
Hemifield Differences(I): Zoomed

Lower

Upper
Contour integration:

- Performance is higher in lower hemifield.
- Performance gap is larger for task requiring co-circular lateral interactions.
What has been shown?

1. **Synchrony** in model accounts for human performance.

2. Synchrony is established through *lateral connections*.

3. The lateral connections are a result of *self-organization*.

4. **Changes in input** cause difference in structure and performance.
Summary(2): Predictions

1. Correlation of MUA sequences can represent perceptual grouping.

2. V1 mechanisms can account for edge-induced illusory contours.

3. Layered architecture in V1 may be due to different functional requirements: (1) self-organization and (2) grouping.

4. Input difference can cause structural changes, and result in altered performance.

5. Straight inputs can cause co-circular lateral interaction properties to emerge.
Future Work

1. Neuroscience:
   - Verify functional connection statistics.
   - Connections before, during, and after development.
   - Effect of disrupted neural synchrony on perception.

2. Psychophysics:
   - Extend the model further for full stimulus dimensions.
   - Role of higher areas on task performance.

3. Intelligent Systems:
   - Application to real-world images.
   - Higher module for activity interpretation.
   - Multi-modal integration.
Conclusion

- Model based on synchronization and self-organization.

- Accounts for:
  1. structural formation (development) and
  2. functional mechanisms in contour integration tasks.

- Contributes to:
  1. understanding the neural mechanisms of P.G.
  2. laying a foundation for artificial vision systems.
Extra Slides
INF vs. Dynamic Threshold

\[ \frac{dx}{dt} = -x + \frac{I}{R} \]
\[ x(t) = IR(1 - e^{-t/R}) \]

vs.
\[ T(t) = e^{-t/R} \]
Correlation coefficient between MUAs $X$ and $Y$:

$$r = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{\sqrt{\sum_i (X_i - \mu_X)(Y_i - \mu_Y)}}{\sqrt{\sum_i (X_i - \mu_X)^2} \sqrt{\sum_i (Y_i - \mu_Y)^2}}$$
Human Contour Integration

Figure 7. Length = 80% of display diameter. Open circles: contour detection accuracy for random contours, as a function of contour shape (fractal exponent), average contour amplitude (RMS amplitude), and magnitude of orientation jitter of the elements (Orientation jitter range). Solid stars: predicted performance of a two-parameter image structure model.

Geisler et al. (2001)
Neurons responding to mixed inputs are not measured.
Network of Spiking Neurons

Summary of spiking neuron behavior in a network:

- Excitation with fast decay causes synchrony.
- Inhibition with fast decay causes desynchrony.
- Noise helps desynchrony.
- Refractory period helps overcome high levels of noise.