Contour Grouping: From Saliency Network to Global Optimal Regions and Boundaries

Guangyu Zhu

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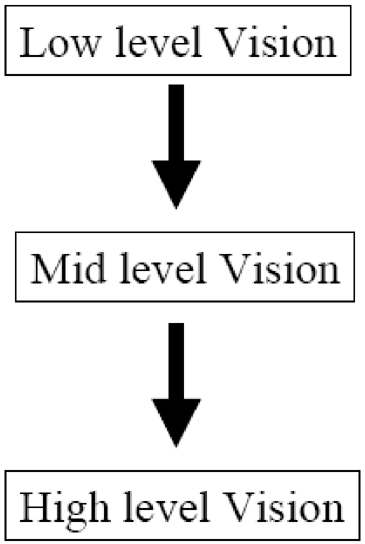
UNIVERSITY OF MARYLAND

Outline

- Motivation
- Saliency network (Shashua & Ullman, 1988)
- Analysis of saliency network (Alter & Basri, 1998)
- Globally optimal regions and boundaries (Jermyn & Ishikawa, 1999)
- Conclusion

Introduction



Determination of local image properties

- Smoothing/Diffusion
- Edge Detection
- Color
- Texture

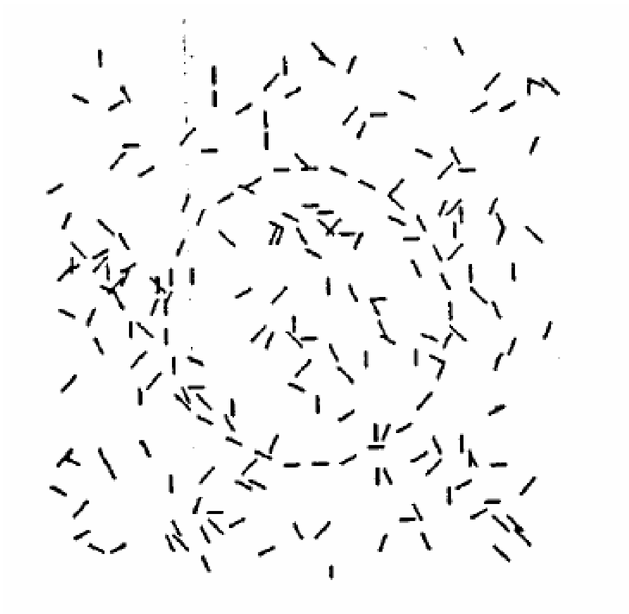
Convert low level data into objects and scene description

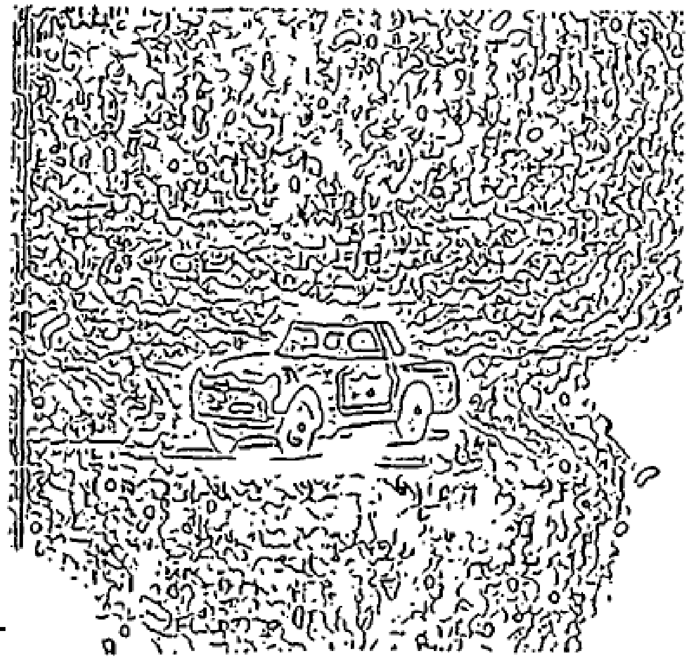
- Boundaries
- Regions
- Surfaces
- Objects

Inference of scene description
Semantic analysis and interpretation

Boundary-based segmentation

- *Boundary-based* approaches
  - Often sufficient to separate objects from background
  - Treats properties such as smoothness very naturally
  - Structural saliency is a property of the structure as a whole





Region-based segmentation

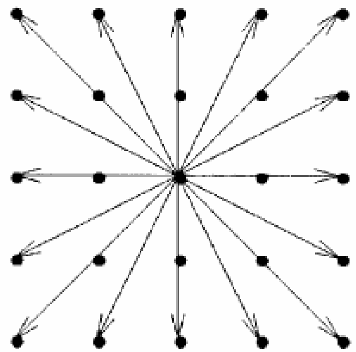
- *Region-based* methods consider distinguishing local properties, such as color and texture.
- We will look at an approach that can combine features of region- and boundary-based approaches.

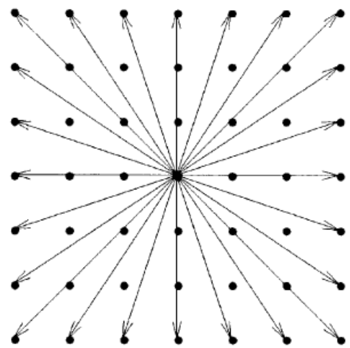
Saliency network (Shashua & Ullman, 1988)

- Proposed a measure that evaluates the "saliency" of a curve
  - The measure monotonically increases with the length of the evaluated curve
  - Decreases monotonically with the *energy* (the total squared curvature) of the curve
  - Perform gap completion on fragmented curves
- Defined the "saliency map" of an image to be an image in which the intensity value of each pixel is proportional to the score of the most salient curve starting from that pixel.
- Considered it as a useful pre-attentive step

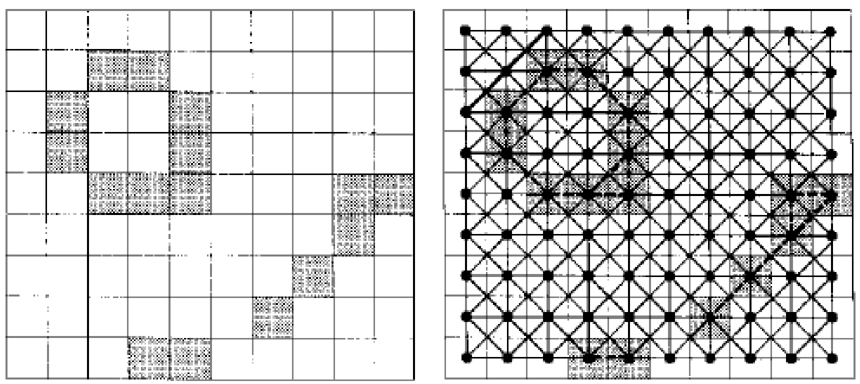
Local orientation of saliency network

- Local connectivity of Shashua and Ullman's Saliency Network





- Saliency network illustrated using only 8 orientations



Saliency of a curve

- The saliency of a curve Γ of length $N+1$ is defined by

$$\Phi(\Gamma) = \sum_{j=i}^{i+N} \sigma_j \rho_{ij} C_{ij}, \qquad (1)$$

where

$$\sigma_j = \begin{cases} 1, & \text{if } p_j \text{ is actual} \\ 0, & \text{if } p_j \text{ is virtual} \end{cases}$$

and

$$\rho_{ij} = \prod_{k=i}^{j} \rho_k = \rho^{g_{ij}},$$

and

$$C_{ij} = e^{-K_{ij}}, \qquad K_{ij} = \int_{p_i}^{p_j} \kappa^2(s)\, ds,$$

Saliency of an element

- The saliency of an element p_i

$$\Phi(i) = \max_{\Gamma \in \mathcal{C}(i)} \Phi(\Gamma), \qquad (2)$$

- $C(i)$ is the set of all curves starting from p_i. So $|C(i)| = k^N$.
- Shashua & Ullman explicitly assumed extensibility in the solution to reduce this search space to kN.

$$\Phi_N(i) = \max_{p_j \in \mathcal{N}(i)} F(i, j, \Phi_{N-1}(j)), \qquad (3)$$

- Is this assumption always valid?

Saliency of an element

- The saliency of an element p_i computed by recurrence

$$\Phi_N(i) = \sigma_i + \rho_i \max_{p_j \in \mathcal{N}(i)} C_{ij} \Phi_{N-1}(j). \qquad (4)$$

- If the extensibility assumption is true, this solution is optimal over all curves that are less than or equal to *N* elements long by Shashua and Ullman's saliency measure.

Analysis of saliency network

- Alter and Basri (1998) introduced a continuous version of saliency function

$$\Phi(\Gamma) = \int_0^l \sigma(s)\rho(0,s)C(0,s)ds,$$

where

$$\sigma(s) = \begin{cases} 1, & \text{if } \Gamma(s) \text{ is actual} \\ 0, & \text{if } \Gamma(s) \text{ is virtual} \end{cases} \qquad \begin{aligned} \rho(s_1, s_2) &= \rho^{g(s_1,s_2)} \\ C(s_1, s_2) &= e^{-K(s_1,s_2)}, \end{aligned}$$

$$g(s_1, s_2) = \int_{s_1}^{s_2} (1 - \sigma(t))dt, \qquad (7)$$

$$K(s_1, s_2) = \int_{s_1}^{s_2} \kappa^2(t)dt. \qquad (8)$$

- Given a curve Γ that consists of two concatenated sections Γ_1 and Γ_2

$$\Phi(\Gamma) = \Phi(\Gamma_1) + \rho^{g(\Gamma_1)} e^{-K(\Gamma_1)} \Phi(\Gamma_2), \qquad (9)$$

Convergence & complexity

- Cycles are considered curves with infinite lengths
- Convergence is guaranteed for cycles
- The time complexity is $O(p^2k^2)$.
- Overall, saliency network is efficient as it searches exponential space of possible curves in polynomial time

Issues with saliency network

- Problems with the extensibility assumption
  - The network must make a single choice at every junction
  - Serious problem in extracting more than one object contour
  - Subject to discretization problem
  - Restrict the set of functions that can be possibly used as saliency measure
  - Other more implicit issues:
    - How to weight between length and smoothness? Shashua & Ullman used $\rho = 0.7$.
    - Not scale invariance
    - Large gap vs. small gaps with same total length

How to combine region with boundary

- Getting a globally optimal grouping of contours based on selective boundary measures is difficult
- If we further assume that the interested regions are closed, how to incorporate region features with boundaries?
- Two questions are key
  - A functional form that allows both region-based and boundary-based features to be globally optimized
  - Efficient algorithms to find solutions to such global optimization problem

Global optimal regions and boundaries

- Jermyn & Ishikawa (ICCV'99) proposed a general energy functional in the form

$$E(I, \mathcal{R}) = \frac{\left|\int_{\mathcal{R}} f \, dx \, dy\right|}{\int_{\partial\mathcal{R}} g \, ds} \quad (1)$$

  where *R* denotes a region and ∂*R* is its boundary
- *f* can be any real-valued function in the image space.
- The numerator is a measure of the "flow" into or out of the region.
- The denominator is a generalized measure of the length of the boundary and also functions as a smoothing term
- The solution to this optimization problem gives the global maximum of *E* over all possible regions *R*.

Global optimal regions and boundaries

- If function *f* in the numerator can be expressed as the divergence of some vector function $\vec{A}$, i.e. $\vec{\nabla} \cdot \vec{A} = f$. The energy functional can be rewritten as

$$E(I, \partial\mathcal{R}) = \frac{\left|\int_{\partial\mathcal{R}} \hat{n} \cdot \vec{A}\, ds\right|}{\int_{\partial\mathcal{R}} g\, ds} \qquad (2)$$

- Equation (2) allows us to include both boundary and region information in our model
- Averaging the weight of the boundary over a measure of its length seems to have two advantages
  - Remove certain dependency on contour length
  - Able to find the minimum mean weight cycle using algorithm that runs in polynomial time

Global optimal regions and boundaries

- Is the energy functional general enough?
- In fact, *f* in equation (1) can be any integrable function. In particular, it can be the convolution of the image with any filter F: $f(p) = I * F(p)$
- In other words, we can find closed regions with specific properties by smartly choosing the right *f*
- $\boldsymbol{f = I * G}$: Globally maximum intensity regions.
- $\boldsymbol{f = I * \vec{\nabla}^2 G}$: Region with the largest absolute value of the integrated Laplacian of the smoothed intensity.
- $|\boldsymbol{f = I * \vec{\nabla}^2 G}|$: Contrast-reversing region
- $|\boldsymbol{f = I * \vec{\nabla} G}|^{-1}$: Globally most homogenous intensity

Global optimal regions and boundaries

- Example using a synthetic image

(a) (b) (c)

$$f = I * \vec{\nabla}^2 G \qquad |f = I * \vec{\nabla}^2 G|$$

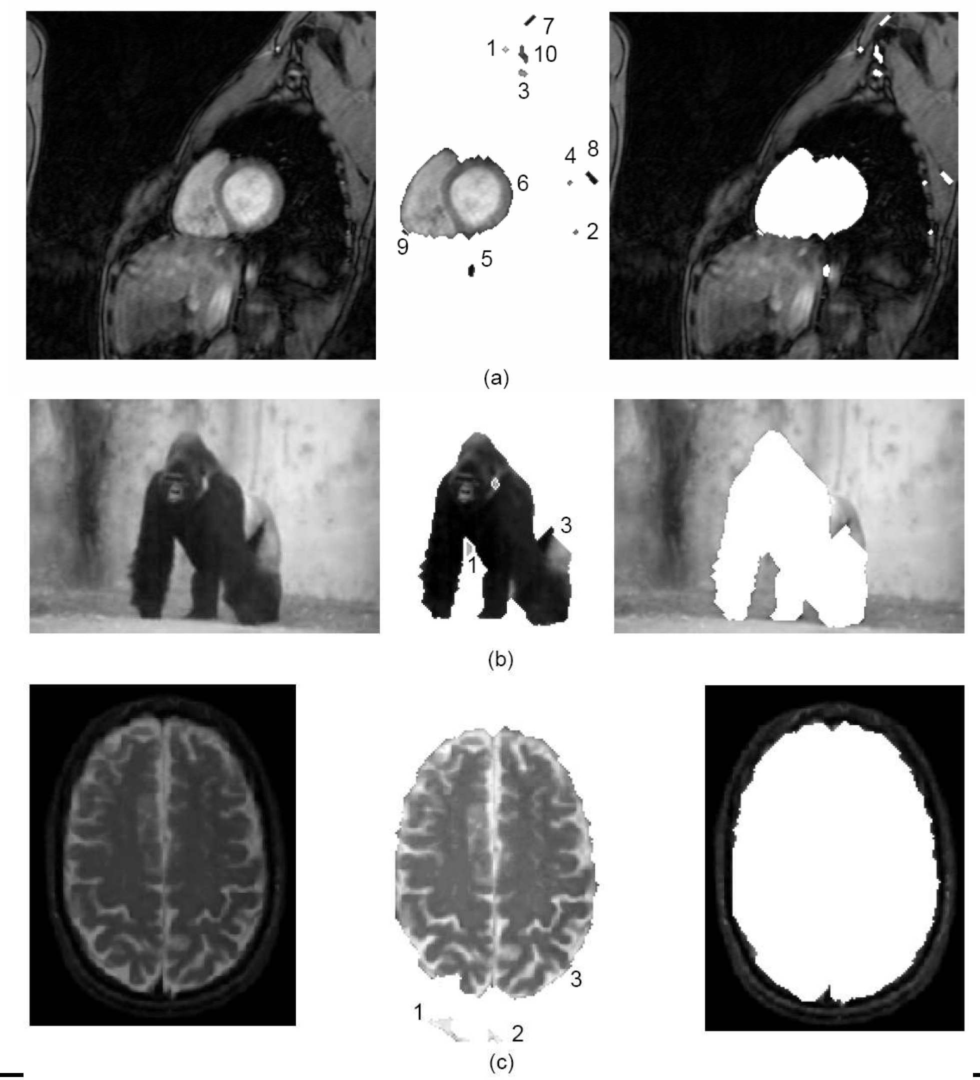
Global optimal regions and boundaries

- Still have to show how to cast the problem into a minimum mean weight cycle problem

$$E(I, \mathcal{R}) = \frac{\left|\int_{\mathcal{R}} f\, dx\, dy\right|}{\int_{\partial\mathcal{R}} g\, ds} \qquad E(I, \partial\mathcal{R}) = \frac{\left|\int_{\partial\mathcal{R}} \hat{n} \cdot \vec{A}\, ds\right|}{\int_{\partial\mathcal{R}} g\, ds}$$

- Maximizing energy in (1) and (2) is equivalent to minimizing the whole thing without modulus sign in two possible orientation of contour integration.
- We transform the energy minimization problem edge into a minimum mean weight cycle problem on a directed graph
- Look at the whiteboard

Global optimal regions and boundaries



Conclusion

- Saliency network is an efficient mechanism for directing attention to a single object based on length and smoothness.
- Its extensibility structure greatly restrict the set of functions that can be used as saliency measure.
- Global optimal regions and boundaries is a more flexible and general approach when dealing with closed contours.
- For grouping contours by semantic content, global optimization is generally not sufficient. High-level knowledge that gives local constraints are unavoidable.

References

1. A. Sha'ashua and S. Ullman, “Structural saliency: The detection of globally salient structures using a locally connected network,” ICCV'88, pp. 321-327, 1988.
2. T.D. Alter and Ronen Basri, "Extracting Salient Curves from Images: An Analysis of the Saliency Network," International Journal of Computer Vision, 27(1): 51-69, 1998.
3. Ian H. Jermyn, Hiroshi Ishikawa, "Globally Optimal Regions and Boundaries," ICCV'99, September 20-27, 1999.
4. L. R.Williams, K. K. Thornber, “A Comparison of measures for detecting natural shapes in cluttered backgrounds,” ECCV'98, pp. 432–448, June, 1998.

Question?