Towards Segmenting Images of Natural Scenes with Spectral Graph Partitioning

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Complexity of Natural Scenes
Use of Segmentation: from Pixels to Regions
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Fundamental Issues

• What feature attributes to extract from the image? raw intensity? filter responses? edges? histograms? ...
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  similarity? proximity? curvilinearity? convexity? ...
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- What feature attributes to extract from the image? raw intensity? filter responses? edges? histograms? ...

- What grouping cues to employ on the features? similarity? proximity? curvilinearity? convexity? ...

- What criterion to apply to these grouping cues? local goodness of grouping? ... global goodness of grouping? ...
Two Difficulties: Texture vs. Contour Completion

- Filter responses
- Distribution similarity
- Feature clustering
- Features
- Cues
- Criterion

(HofmannPuzichaBuhmann98,...)
(MahamudWilliamsThornberXu03,...)

- Edge elements
- Curvilinearity
- Continuity, closure
More Generative Models

(a) input image

(b) regions

(c) curves

(d) free curves

(e) parallel curves

(f) trees

(TuZhu02)
More Discriminative Features for Better Edges

(MalikBelongieLeungShi01, MartinFowlkesMalik02, MartinFowlkesTalMalik01)
Alternative: Deal at Integration Level

- Texture segmentation methods are too coarse-scale for contour completion.
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- Contour completion methods are too fine-scale for texture segmentation.
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- Monitoring both texture and contour completion through either more models or more features introduces wasted computation and cross interference.

Feature = edges
Grouping cue = elongated intervening contours
Grouping criterion = spectral graph-cut criterion
Alternative: Deal at Integration Level

• Texture segmentation methods are too coarse-scale for contour completion.

• Contour completion methods are too fine-scale for texture segmentation.

• Monitoring both texture and contour completion through either more models or more features introduces wasted computation and cross interference.

• Alternative: examine grouping across scales!
  
  feature = edges
  grouping cue = elongated intervening contours
  grouping criterion = spectral graph-cut criterion
Key Insight: Scale-Invariant Segmentation

1. Texture is smoothed out.
Key Insight: Scale-Invariant Segmentation

2. Smaller gaps are easier to complete.
Model Outline

- Evaluate goodness of grouping at a single scale
  1. Brief introduction to spectral graph cuts
  2. Grouping cue: elongated intervening contours
Model Outline

- **Evaluate goodness of grouping at a single scale**
  1. Brief introduction to spectral graph cuts
  2. Grouping cue: elongated intervening contours

- **Relate goodness of grouping across scales**
  1. Medial axes as hubs linking pixels across scales
  2. Projection of grouping cues to original pixel scale
Model Outline

- Evaluate goodness of grouping at a single scale
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- Integrate over multiple scales
  1. Graph architecture
  2. Optimizing the overall goodness of grouping
Grouping by Graph Cuts: 1. Representation
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Step 1: Build a weighted graph $W$

\[ W(p, q) = e^{-\frac{\text{intensity difference}(p, q)^2}{\sigma}} \]
Grouping by Graph Cuts: 1. Representation

\[ W(p, q) = e^{-\frac{\text{intensity difference}(p,q)^2}{\sigma}} \]

Step 1: Build a weighted graph \( W \)
Grouping by Graph Cuts: 2. Criterion

\[
\min \text{ normalized cuts} = \frac{\min \text{ between-group affinity}}{\max \text{ within-group affinity}} \quad \text{(ShiMalik97)}
\]

Step 2: Seek an optimal node partitioning
Grouping by Graph Cuts: 3. Solution

Step 3: Find near-global optima to this NP-complete problem
Grouping by Graph Cuts: 3. Solution

eigenvectors of $W \longrightarrow$ discretization (YuShi03)

Step 3: Find near-global optima to this NP-complete problem
Grouping Cue: Elongated Intervening Contours

1. Four rules in one: intensity similarity, convexity, closure and curvilinearity
2. Curvilinearity by carving spatial relationships among pixels that define the boundaries.

Naive Intervening Contours
Grouping Cue: Elongated Intervening Contours

\[ W(p, q) = e^{-\frac{\max_{t \in (0,1)} |\text{contour}(p + t \cdot q)|^2}{\sigma}} \]

1. Four rules in one: intensity similarity, convexity, closure and curvilinearity
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Naive Intervening Contours

Elongated Intervening Contours
Grouping Cue: Elongated Intervening Contours

$W(p, q) = e^{-\frac{\max_{t \in (0,1)} \text{contour}(p+t \cdot q)^2}{\sigma}}$

1. Four rules in one: intensity similarity, convexity, closure and curvilinearity

2. Curvilinearity by carving spatial relationships among pixels that define the boundaries.
Scale-Invariant Organization of Dot Arrays

\[ \text{Trivial global scaling invariance:} \]

Two sets of dots are in one-to-one correspondence across scales!
Scale-Invariant Organization of Dot Arrays

(KubovyHolcombe98)

Trivial global scaling invariance: Two sets of dots are in one-to-one correspondence across scales!
Scale-Invariant Organization of Dot Arrays

Trivial global scaling invariance:
Two sets of dots are in one-to-one correspondence across scales!

(KubovyHolcombe98)
From Image to Weighted Graph: Scale 1
From Image to Weighted Graph: Scale 1
From Image to Weighted Graph: Scale 2
From Image to Weighted Graph: Scale 2
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From Image to Weighted Graph: Scale 2
Comparison of Grouping Cues at Two Scales
Comparison of Grouping Cues at Two Scales

conflicting for boundary pixels!

consistent for interior pixels!
Correspondence of Pixels thru Interior Buddies

Map each pixel to its interior buddy:

$$B(p) = \text{center of weighted mass at } p\text{'s neighbourhood}.$$
Emergence of Interior Buddies as Medial Axes
Projecting Grouping Cues to A Finer Scale

\[ W_2(p, q) = W_2(B(p), B(q)) \]
Integration Over Multiple Scales: 1. Affinity

Step 1: Compute affinity $W_s$ based on edges at scale $s$. 
Integration Over Multiple Scales: 2. Buddy

Step 2: Compute buddy $B_s$ based on $W_s$. 
Integration Over Multiple Scales: 3. Projection

Step 3: Project affinity $W_s$ to the original pixel scale.
Integration Over Multiple Scales: 4. Criterion

Step 4: Seek an optimal cut on the total graph $W$. 

$\varepsilon(W_{1\rightarrow 1})$  $\varepsilon(W_{2\rightarrow 1})$  $\varepsilon(W_{3\rightarrow 1})$
Integration Over Multiple Scales: 4. Criterion

\[ \varepsilon_{\text{total}} = \varepsilon(W_{1\rightarrow 1}) + \varepsilon(W_{2\rightarrow 1}) + \varepsilon(W_{3\rightarrow 1}) \]

Step 4: Seek an optimal cut on the total graph \( W \).
Integration Over Multiple Scales: 4. Criterion

\[ \varepsilon_{\text{total}} = \varepsilon(W), \quad W = W_{1\rightarrow1} + W_{2\rightarrow1} + W_{3\rightarrow1} \]

Step 4: Seek an optimal cut on the total graph \( W \).
Results: Eigenvectors and Segmentations
Results on Typical Texture and Contour Images
Comparison: Canny, Pb Edges, Segmentations
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Take Home Message

Boundaries manifest themselves in multiscale edges that separate interior pixels consistently, a characteristic that texture edges lack, while illusory contours possess just as well as ordinary boundaries do.
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