Contour Detection and Hierarchical Image Segmentation – Some Experiments

CS395T – Visual Recognition

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Overview

• Understanding the method better:
  – The importance of thresholding the output
  – Understanding the inputs better
  – Understanding the UCM

• Pushing for boundaries:
  – Types of difficult inputs
  – Difficult input examples
Warm-up: choosing the right threshold

\[ k = 0.4 \]
Warm-up: choosing the right threshold

\[ k = 0.1 \]
Warm-up: choosing the right threshold

\[ k = 0.8 \]
So what goes into the OWT?


The Features

• Difference in feature channels on the two halves of a disc of radius $\sigma$ and orientation $\theta$.

• Feature channels in our case:
  – Color gradients
  – Brightness gradients
  – Texture gradients

• Comparison between the two disc halves using $\chi^2$ distance.
The basic signals

• Color/brightness channels based on Lab color space.
• Repeatedly generated at different scales (different $\sigma$ radii values - $\frac{\sigma}{2}$, $\sigma$, $2\sigma$).
• All in all we get 13 different inputs.
Illustration n. 1:
Color gradient \( a \) (red-green scale)
Illustration n. 2:
Color gradient $a$, different $\sigma$ value

$\theta = \frac{\pi}{4}$

$\theta = \frac{-\pi}{4}$

$max_{\theta} \{cga\}$

$\theta = 0$
Illustration 3:
Brightness gradient (light-dark scale)

$\theta = \frac{\pi}{2}$

$\theta = -\frac{\pi}{4}$

$\max_{\theta} \{cga\}$

$\theta = \frac{\pi}{2}$
Illustration 4: Texton Map
Multiscale $Pb$ and Spectral/Global $Pb$

• The features are linearly combined to create a unified signal, the multiscale Pb input.
• They are then “globalized” spectrally.
• An affinity matrix $w$ is constructed with $W_{ij}$ being the maximal value of $mPb$ along the line connecting $i$ and $j$.
• Generalized eigenvectors are then extracted and combined (after processing) with the local $Pb$ data to create the final input for the OWT.
$mPb$ vs. $gPb$
(In practice we sample 8 orientations...)

\[ gPb = \max_\theta \{ \theta = \left[ 0, \frac{\pi}{8}, \frac{\pi}{4}, \frac{3\pi}{8}, \ldots, \frac{7\pi}{8} \right] \} \]
(In practice we sample 8 orientations...)

\[ g_P b = \]
Playing with the orientations a bit...
Playing with the orientations a bit...
Using less than 8 orientations

2 orientations
Using less than 8 orientations

4 orientations (in this case it’s enough)
The Ultrametric Contour Map

- The basic idea is to organize and merge sub-regions hierarchically and iteratively.
- At each point we merge two regions with the weakest boundary between them.
- The result is a dendrogram of nested regions.
Example 1
Potentially Difficult Input

• We would like to test the OWT-UCM method against problematic input.
• See where it might break.
warming up - blurring
Potentially Difficult Input II

• Blurring isn’t very interesting – doesn’t reflect the kind of challenges the algorithm is likely to face.

• What realistic problems exist?
  – Difficult patches
  – Complex, contour-rich images
  – Not enough color/texture information
Difficult Input – abstract art

$k = 0.4$
Difficult Input – abstract art

\[ k = 0.1 \]
Difficult(er) Input – abstract(er?) art

\[ k = 0.4 \]
Difficult(er) Input – abstract(er?) art

\[ k = 0.1 \]
Another Difficult Example

- Occlusion
- Similarity of objects in image:
  - Similar textures
  - Similar colors
  - Contour lines blend
Another Difficult Example

\[ k = 0.4 \]
Another Difficult Example

\[ k = 0.1 \]
Another Difficult Example

\[ k = 0.2 \]
Sneaking a look under the hood

• Possibly we need to weight elements differently in certain cases...
Summary

• Studied some of the technical aspects of the method:
  – Threshold selection
  – Understanding the input data
  – Illustration of UCM in action

• Tested the method against difficult input:
  – Problematic contours
  – Complex images
  – Cases where features aren’t informative enough
  – Many similar items occluding one another
References

- Class notes for 16-721: Learning-Based Methods in Vision, taught by Prof. Alexei Efros, CMU.
- Class notes for CS 143: Introduction to Computer Vision, taught by Prof. James Hayes, Brown.