Superpixels

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Overview

Superpixel (SP): What & why?

'A **Superpixel** groups raw pixels into *perceptually meaningful atomic regions*'

- SP map is a more *natural* representation of a visual scene
  - Pixels are not natural entities
  - Pixel-grid is an inefficient representation
  - SPs provide richer feature descriptors (histograms, shape factors, spatial relationships etc.)
- Ideal SP map has some desirable properties [Ren, 2003]:
  1. Computationally efficient
  2. Representationally efficient
  3. Perceptually meaningful
  4. Near-complete

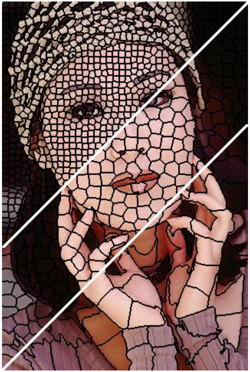


Figure: *Image segmented using SLIC into superpixels of size 64, 256, and 1024 pixels (approximately) [Achanta et al, 2012].*

SP methods

- There are *many* methods for generating Superpixels
- Some are better suited to particular applications than others
- Desirable SP properties:
  1. Adhere well to image boundaries
  2. Generated as efficiently as possible
  3. Do not negatively impact performance of subsequent steps

Graph-based	**Gradient-ascent**
Pixels as node in a graph	Start from an initial clusters
Distance of pixel from centroid feature	Iteratively refine clusters
Edge weights represent affinities between pixel pairs	Cluster on pixel colour and/or Cartesian coordinates
Minimise a cost function over graph	SP formed when convergence criterion met

Table: *Two broad categories of SP methods*

Comparison of Graph Based Algorithms

Algorithm	Complexity	Advantages	Drawbacks
Normalised Cuts [Shi & Malik, 2000]	$O(N^{\frac{3}{2}})$	Regularly sized, shaped, distributed SPs	Poor boundary adherence,
Agglomerative Clustering [Felzenszwalb et al, 2004]	$O(NlogN)$	Good boundary adherence	SP with very irregular sizes/shapes
Optimal Paths [Moore et al, 2008]	$O(N^{\frac{3}{2}} logN)$	Regular lattice of SPs	Pre-computed boundary maps required
Global Optimisation [Veksler et al, 2010]	$O(NlogN)$	Trades tesselation with boundary accuracy/better efficiency	Forces an artificial structure on image that may not exist

Table: A comparison of graph based algorithms

Comparison of Gradient-ascent Algorithms

Algorithm	Complexity	Advantages	Drawbacks
Mean shift [Comaniciu et al, 2002]	$O(N^2)$	Robust against transformations	Irregularly shape SPs of non-uniform size
Quick shift [Vedaldi et al, 2008]	$O(dN^2)$	Good boundary adherence	No control over size/number of SPs
Watershed [Vincent et al, 1991]	$O(NlogN)$	Good boundary adherence	Highly irregular SPs, sensitive to extrema
Turbopixels [Levinshtein et al, 2009]	$\sim O(N)$	SPs regularly sized, shaped	Relatively poor boundary adherence
SLIC [Achanta et al, 2012]	$O(N)$	Control over SP density, compactness, adherence	Additional parameters to consider

Table: A comparison of gradient-ascent algorithms

Comparison of SP methods

Figure: *Comparison of three SP methods.*

Agglomerative Clustering - [Felzenszwalb et al, 2004]

- Performs an *agglomerative clustering* of pixels as nodes on a graph
- Each pixel starts in its own segment
- Algorithm merges segments based on evidence for a boundary between two segments
- Adheres well to boundaries in practice
- Produces SP with irregular shapes and sizes
- No explicit control over SP quantity or their compactness

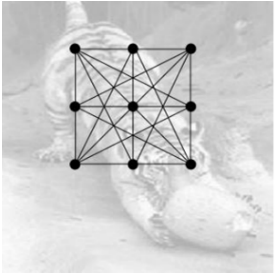


Figure: *Graph-based image segmentation.*

Quick Shift - [Vedaldi et al, 2008]

- A fast *mode-seeking* segmentation scheme
- Associate each pixel to a mode of an underlying p.d.f.
- Identifies pixel clusters in joint spatial and colour dimensions
  1. Estimate a density for each pixel
  2. Follow the gradient of the density to assign each pixel to a mode
  3. Modes represent the final clusters

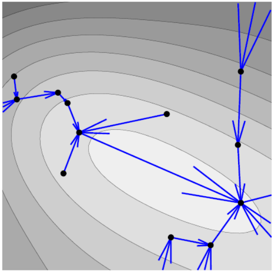


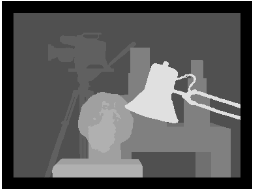
Figure: *Quick shift: Assignment of data points to mode using underlying density [Vedaldi et al, 2008].*

SLIC - [Achanta et al, 2012]

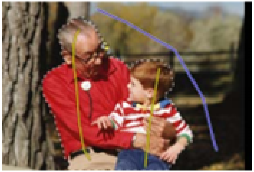
Figure: *Example images segmented using SLIC.*

- It is a faster adaptation of k means clustering
- Initially k cluster centers are sampled on a regular grid
- Cluster centers are moved to avoid centering a SP on an edge
- Each pixel is associated with the nearest cluster center whose search region overlaps its location
- Cluster centers are adjusted to the mean vector of all the pixels belonging to the cluster
- Iterate the assignment and update steps until the error converges
- Disjoint pixels can be reassigned to nearby SP to enforce connectivity

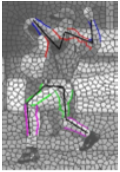
Current Applications



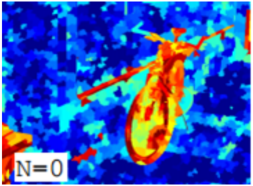
(a) Depth estimation - [Zitnick & Kang, 2007]



(b) Segmentation - [Li et al, 2004]



(c) Body model estimation - [Mori, 2005]



(d) Object localisation - [Fulkerson et al, 2009]

Any questions?

References

J. Shi and J. Malik. Normalized cuts and image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 22 (8): 888 – 905, Aug 2000.

P. Felzenszwalb and D. Huttenlocher. Efficient graph-based image segmentation. International Journal of Computer Vision (IJCV), 59 (2): 167 – 181, September 2004.

A. Moore, S. Prince, J. Warrell, U. Mohammed, and G. Jones. Superpixel Lattices. IEEE Computer Vision and Pattern Recognition (CVPR), 2008.

O. Veksler, Y. Boykov, and P. Mehrani. Superpixels and supervoxels in an energy optimization framework. In European Conference on Computer Vision (ECCV), 2010.

D. Comaniciu and P. Meer. Mean shift: a robust approach toward feature space analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 24 (5): 603 – 619, May 2002.

A. Vedaldi and S. Soatto. Quick shift and kernel methods for mode seeking. In European Conference on Computer Vision (ECCV), 2008.

References

- L. Vincent and P. Soille. Watersheds in digital spaces: An efficient algorithm based on immersion simulations. IEEE Transactions on Pattern Analalysis and Machine Intelligence (PAMI), 13 (6): 583 – 598, 1991.
- A. Levinshtein, A. Stere, K. Kutulakos, D. Fleet, S. Dickinson, and K. Siddiqi. Turbopixels: Fast superpixels using geometric flows. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 2009
- R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, and S. Susstrunk. SLIC superpixels compared to state-of-the-art superpixel methods. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), 34 (11): 2274 – 2282, 2012.
- EECS, University of Michigan, 2012. Segmentation and Clustering. [online lecture slides] Ann Arbor, Michigan. Available at: <`http://wwweb.eecs.umich.edu/vision/teaching/EECS442_2012/lectures/seg_cluster.pdf`>[Accessed 19 February 2015]
- M. Tappen, EECS, University of Central Florida, 2007. E-M and MeanShift. [online lecture slides] Orlando, Florida. Available at: <`http://www.cs.ucf.edu/~mtappen/cap5415/lecs/lec11.pdf`>[Accessed 19 February 2015]

References

- C.L. Zitnick and S.B. Kang. Stereo for Image-Based Rendering Using Image Over-Segmentation. International Journal of Computer Vision, 75: 49 – 65, 2007.
- G. Mori. Guiding Model Search Using Segmentation. Proceedings of IEEE International Conference for Computer Vision, 2005.
- Y. Li, J. Sun, C.-K. Tang, and H.-Y. Shum. Lazy Snapping. ACM Transactions on Graphics, 23 (3): 303 – 308, 2004.
- B. Fulkerson, A. Vedaldi, and S. Soatto. Class Segmentation and Object Localization with Superpixel Neighborhoods. Proceedings of IEEE International Conference for Computer Vision, 2009.
- X. Ren and J. Malik. Learning a classification model for segmentation. In: ICCV. Volume 1., 10 (17), 2003.