Class Segmentation and Object Localization with Superpixel Neighborhoods

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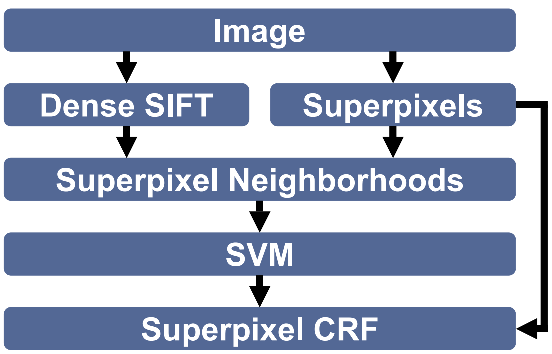
Pixels vs. Superpixels

Why should we consider each pixel?

- Pixels are a side effect of the imaging process.

- The superpixels obtained via quick shift are not fixed in size, shape, or number.

Superpixel Class Segmentation



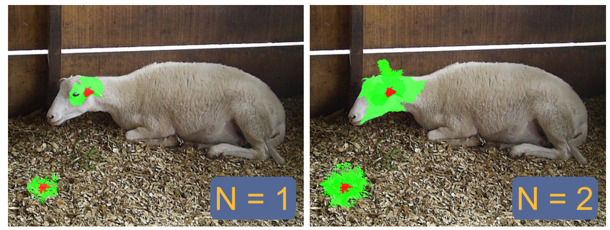
Code Available

- Feature extraction uses VLFeat: http://vlfeat.org/
- MATLAB wrapper for Veksler's GCoptimization toolbox (suitable for solving our superpixel CRFs): http://vision.ucla.edu/~brian/gcmex.html
- MATLAB "block" experiment framework (with these experiments): http://vision.ucla.edu/blocks/

Superpixel Neighborhoods

Neighborhoods regularize the classifier

- Create a per-superpixel histogram.
- Accumulate histograms which are closer than N hops in superpixel graph.

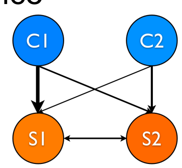


- Since superpixels are not fixed size or shape, the size of the area of influence depends on the image structure.

Superpixel CRF

Incorporate color and confidence

- Multi-label assignment problem solved with graph cuts energy minimization.



$$-log(P(\mathbf{c}|G;w)) = \sum_{s_i \in S} \Psi(c_i|s_i) + w \sum_{(s_i,s_j)\in E} \Phi(c_i,c_j|s_i,s_j)$$

- Unary potential comes from the SVM

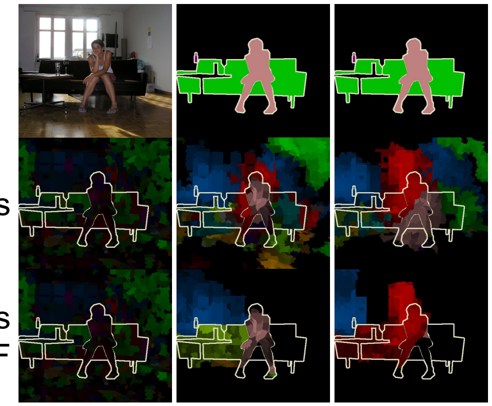
$$\Psi(c_i|s_i) = -log(P(c_i|s_i))$$

- Pairwise potential uses the color difference and shared boundary length (L), and only penalizes when the classes are not equal.

$$\Phi(c_i,c_j|s_i,s_j) = \left(\frac{L(s_i,s_j)}{1+\|s_i - s_j\|}\right)[c_i \neq c_j]$$

- Inference is fast since graph nodes are superpixels.

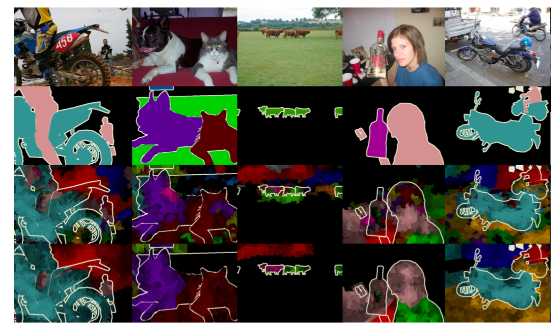
Pascal VOC 2007 Segmentation



Neighbors

Neighbors + CRF

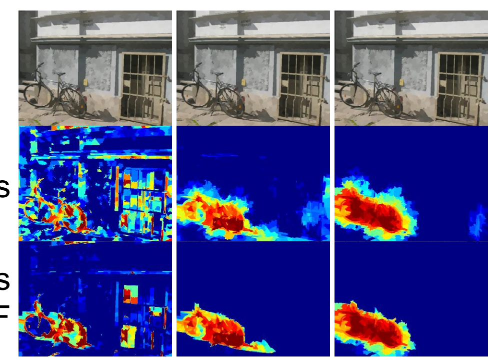
N = 0 N = 2 N = 4



N=2

CRF

Graz-02 Localization



Neighbors

Neighbors + CRF

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