

# SLIC Superpixels

Achanta et al., IEEE PAMI 2012

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# Superpixels



- ▶ small compact groups of pixels
- ▶ oversegmentation - never cross a segmentation boundary / an edge
- ▶ advantages - speed, uniform color and texture for descriptors
- ▶ fast to calculate

# Existing superpixels techniques

- ▶ **normalized cuts** - slow  $O(N^{3/2})$
- ▶ **agglomerative clustering** using minimum spanning tree -  $O(N \log N)$  irregular shape superpixels
- ▶ **optimal splitting paths** using GraphCuts - slow,  $O(N^{3/2} \log N)$  + preprocessing
- ▶ **stitching overlapping patches** - slow
- ▶ **mean shift** - very slow  $O(N^2)$ , no control over superpixel shape
- ▶ **quick shift** - very slow  $O(N^2)$ , no control over superpixel shape
- ▶ **watershed** -  $O(N \log N)$ , no control over superpixel shape
- ▶ **level set geometric flow (TurboPixels)** - in theory  $O(N)$  but in practice slow

TABLE 1  
Summary of Existing Superpixel Algorithms

	GS04 [8]	NC05 [23]	Graph-based			WS91 [28]	Gradient-ascent-based			SLIC
			SL08 [21]	GCa10 <sup>b</sup> [26]	GCb10 <sup>b</sup> [26]		MS02 [4]	TP09 <sup>b</sup> [15]	QS09 [25]	
Adherence to boundaries										
<i>Under-segmentation error</i>	0.23	0.22	-	0.22	0.22	-	-	0.24	0.20	<b>0.19</b>
<i>Boundary recall</i>	<b>0.84</b>	0.68	-	0.69	0.70	-	-	0.61	0.79	0.82
Segmentation speed										
320 × 240 image	1.08s <sup>a</sup>	178.15s	-	5.30s	4.12s	-	-	8.10s	4.66s	<b>0.36s</b>
2048 × 1536 image	90.95s <sup>a</sup>	N/A <sup>c</sup>	-	315s	235s	-	-	800s	181s	<b>14.94s</b>
Segmentation accuracy (using [11] on MSRC)	74.6%	75.9%	-	-	73.2%	-	-	62.0%	75.1%	<b>76.9%</b>
Control over amount of superpixels	No	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes
Control over superpixel compactness	No	No	No	No <sup>d</sup>	No <sup>d</sup>	No	No	No	No	Yes
Supervoxel extension	No	No	No	Yes	Yes	Yes	No	No	No	Yes

# SLIC superpixels

simple linear iterative clustering

- ▶ colors converted to CIELAB  $[l\ a\ b]$
- ▶ pixels represented as  $[l\ a\ b\ x\ y]$
- ▶ main parameter - number of superpixels  $K$
- ▶ based on **k-means** clustering
  - ▶ calculate means of  $k$  groups (superpixels)
  - ▶ assign pixels to means
- ▶ only search in a limited region  $2S \times 2S \implies$  complexity  $O(N)$ 
  - ▶  $S = \sqrt{N/k}$

**Algorithm 1.** SLIC superpixel segmentation

*/\* Initialization \*/*

Initialize cluster centers  $C_k = [l_k, a_k, b_k, x_k, y_k]^T$  by sampling pixels at regular grid steps  $S$ .

**M**ove cluster centers to the lowest gradient position in a  $3 \times 3$  neighborhood.

Set label  $l(i) = -1$  for each pixel  $i$ .

Set distance  $d(i) = \infty$  for each pixel  $i$ .

```
repeat  
  /* Assignment */  
  for each cluster center  $C_k$  do  
    for each pixel  $i$  in a  $2S \times 2S$  region around  $C_k$  do  
      Compute the distance  $D$  between  $C_k$  and  $i$ .  
      if  $D < d(i)$  then  
        set  $d(i) = D$   
        set  $l(i) = k$   
      end if  
    end for  
  end for  
  /* Update */  
  Compute new cluster centers.  
  Compute residual error  $E$ .  
until  $E \leq$  threshold
```

## Distance measure

Combine space and color

$$d_c = \sqrt{(l_j - l_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2},$$

$$d_s = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2},$$

$$D' = \sqrt{\left(\frac{d_c}{N_c}\right)^2 + \left(\frac{d_s}{N_s}\right)^2}.$$

$$N_S = \bar{S} = \sqrt{(N/K)}. \quad D = \sqrt{d_c^2 + \left(\frac{d_s}{\bar{S}}\right)^2} m^2.$$



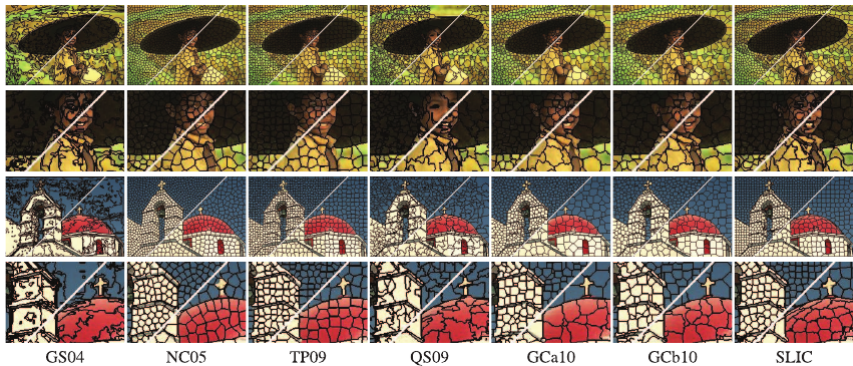
# Postprocessing

- ▶ superpixel  $k$  = pixels assigned to center  $C_k$
- ▶ find connected components
- ▶ “orphaned” components - do not contain a center  $C_i$
- ▶ joined with the nearest cluster

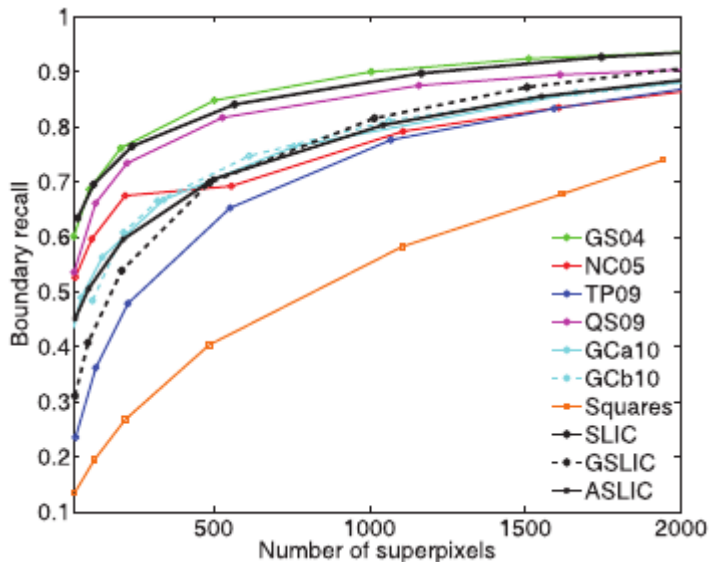
# Complexity

- ▶ Each pixel in at most 8 neighborhoods
- ▶ Small number of k-means iterations ( $<10$ )
- ▶ Complexity  $O(N)$

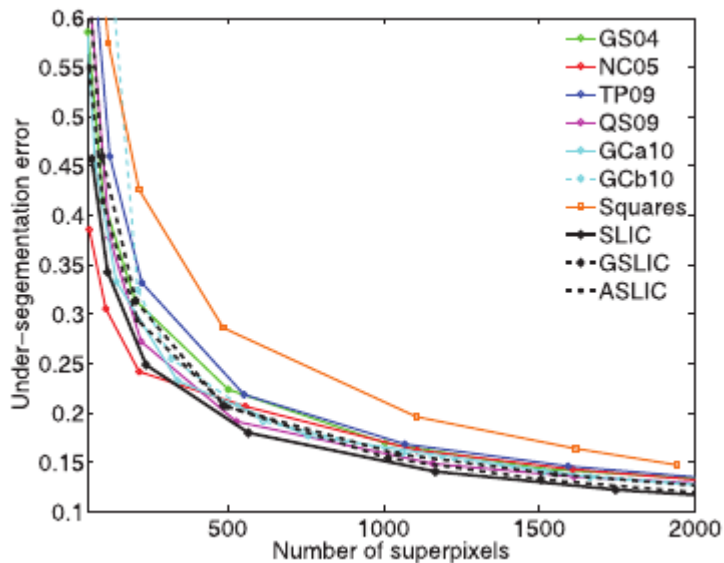
# Examples



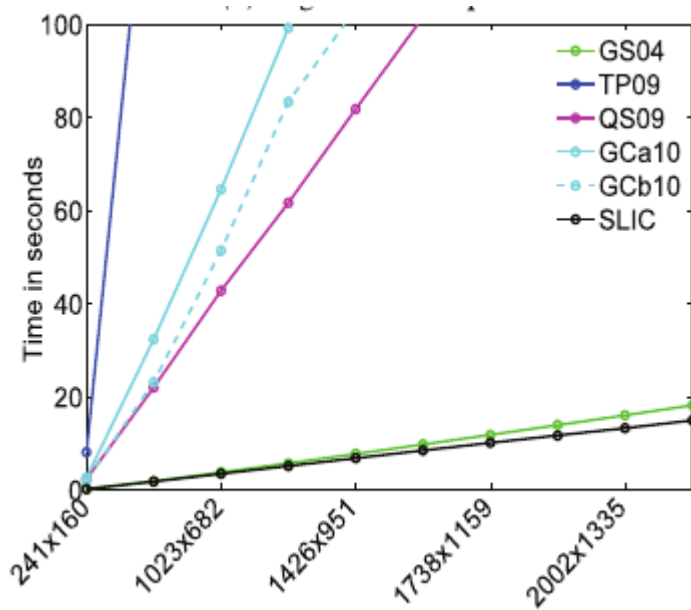
## Boundary recall



# Undersegmentation error



# Speed



# Segmentation example

Gould et al: Multi-Class Segmentation with Relative Location Prior, IJCV 2008

- ▶ calculate superpixels
- ▶ calculate features on superpixels (color, texture, location...) features
- ▶ train a classifier for each object class
- ▶ conditional random field model

original image



ground truth



segmentation of [11] using SLIC

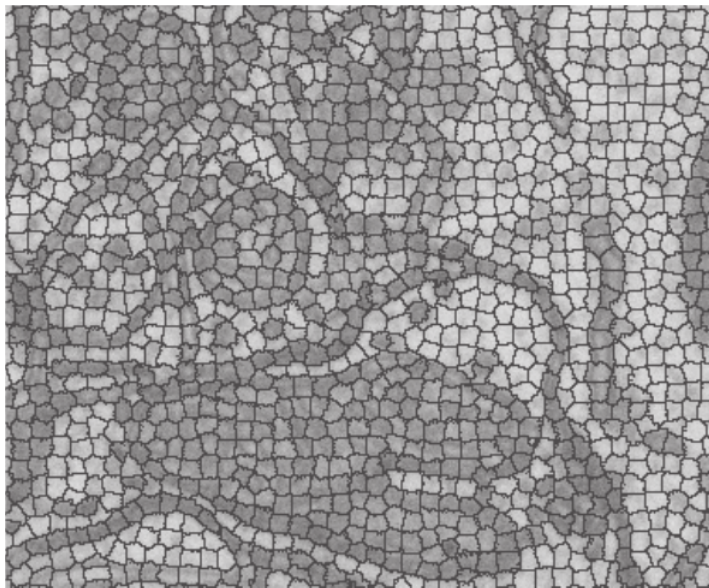


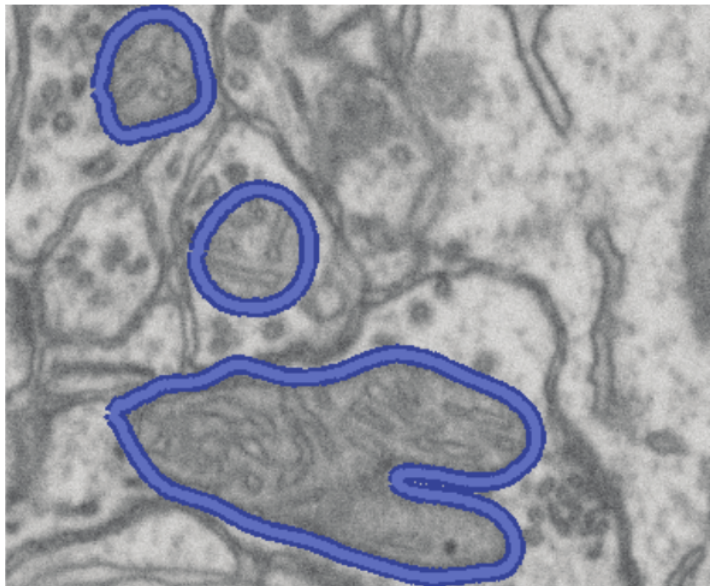


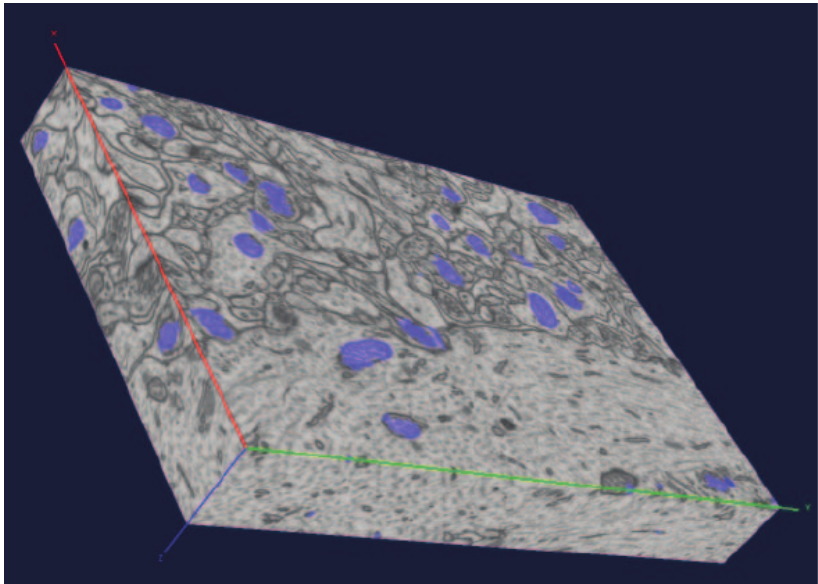
TABLE 2  
Multiclass Object Segmentation on the PASCAL VOC 2010 Data Set

	background	aeroplane	bicycle	bird	boat	bottle	bus	car	cat	chair	cow	dining table	dog	horse	motorbike	person	potted plant	sheep	sofa	train	TV/monitor	Average
SLIC	77.9	49.4	23.1	19.2	24.8	26.1	52.4	44.9	32.9	6.5	35.8	22.3	25.5	21.9	58.1	34.6	26.8	39.9	17.5	38.0	25.3	<b>33.5%</b>
QS09	78.1	45.0	23.3	18.3	25.0	25.5	52.3	45.6	33.2	7.2	36.0	21.5	24.7	21.9	56.9	34.4	26.0	38.9	17.0	37.9	24.8	33.0%

Similar accuracy, SLIC > 10× faster







# Extensions

- ▶ ASLIC - adaptive SLIC
- ▶ GSLIC - geodesic SLIC

# Conclusions

- ▶ Simple and fast method
- ▶ Application results at least as good as for previous methods