Opponent Colors *Revisited*

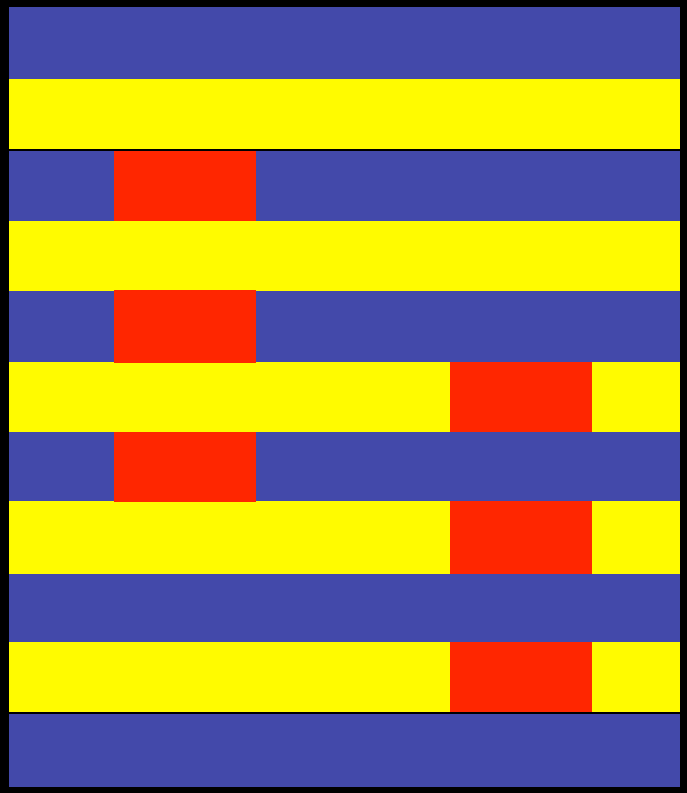
Sabine Süsstrunk
Image and Visual Representation Lab

A small exercise…

- Question: what color is [255,0,0]?

A small exercise…

- Question: what color is [255,0,0]?
- Answer: **red**



Isaac Newton (1666)

http://www.newton.ac.uk/art/portrait.html

https://upload.wikimedia.org/wikipedia/commons/b/bd/Dispersive_Prism_Illustration.jpg

Johann Wolfgang von Göthe…

https://en.wikipedia.org/wiki/File:Goethe_%28Stieler_1828%29.jpg

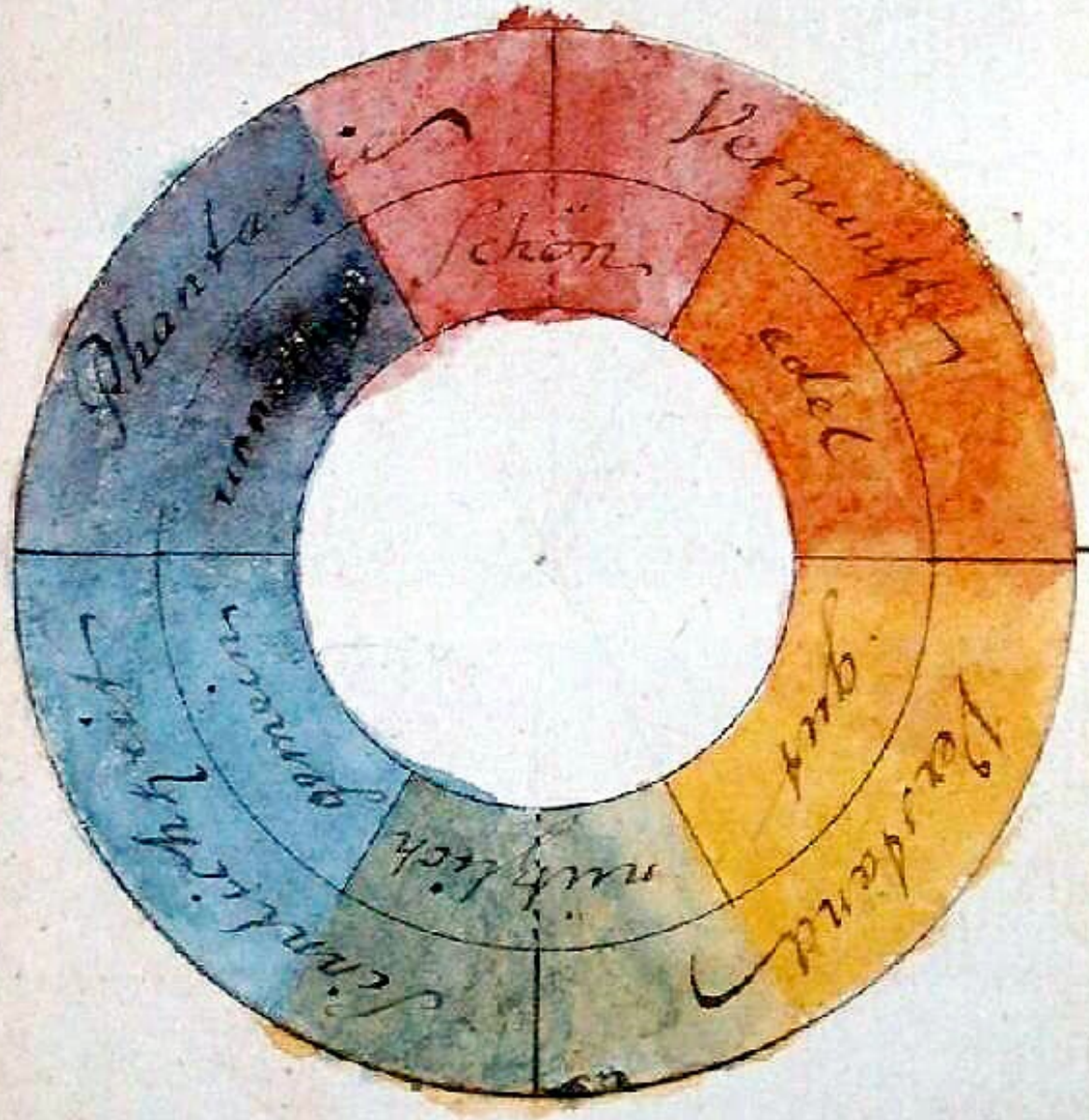
“Along with the rest of the world I was convinced that all the colours are contained in the light; no one had ever told me anything different, and I had never found the least cause to doubt it, because I had no further interest in the subject.”

https://en.wikipedia.org/wiki/Theory_of_Colours

“But how I was astonished, as I looked at a white wall through the prism, that it stayed white! That only where it came upon some darkened area, it showed some colour, then at last, around the window sill all the colours shone... It didn't take long before I knew here was something significant about colour to be brought forth, and I spoke as through an instinct out loud, that ***the Newtonian teachings were false****.”*

Göthe

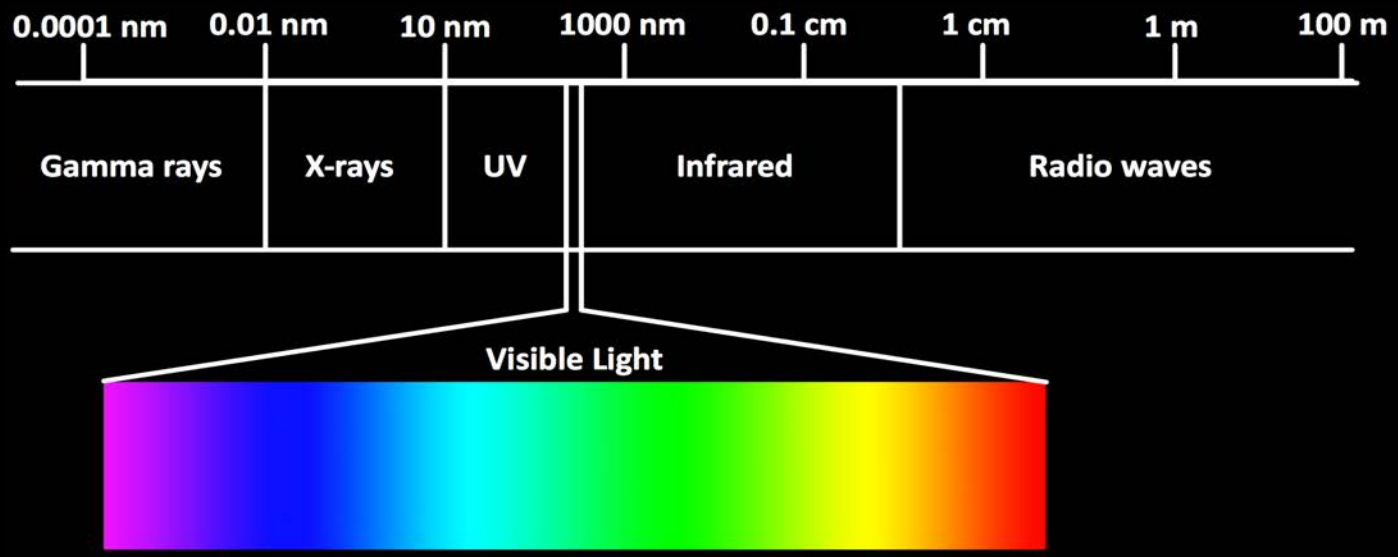
https://en.wikipedia.org/wiki/Theory_of_Colours



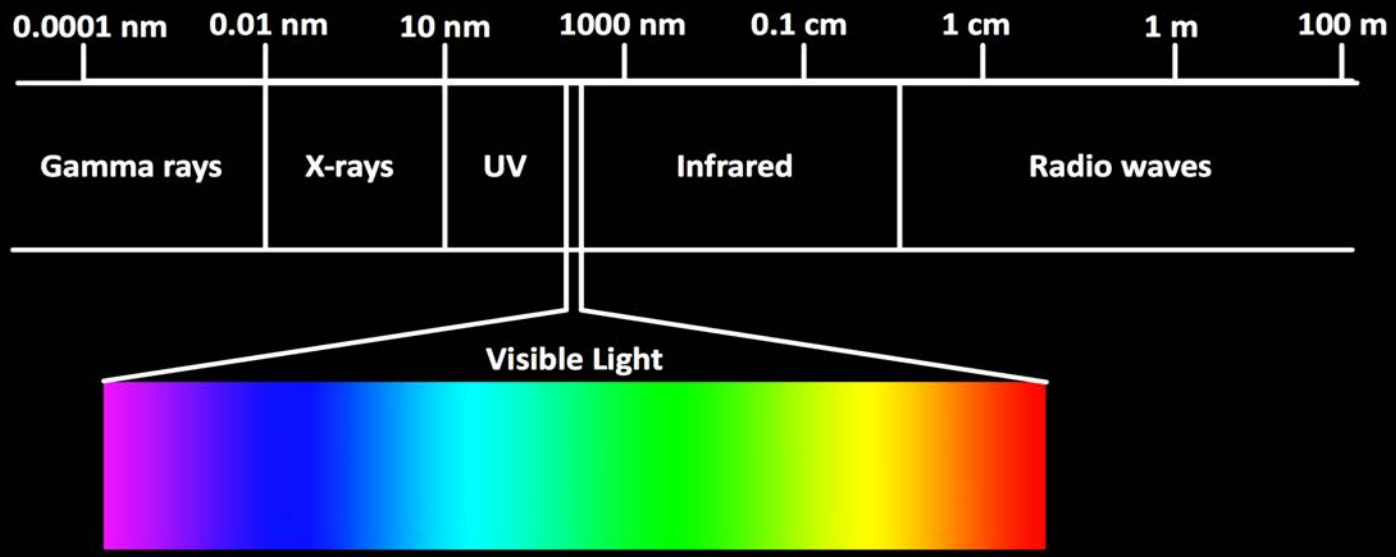
Göthe, 1810

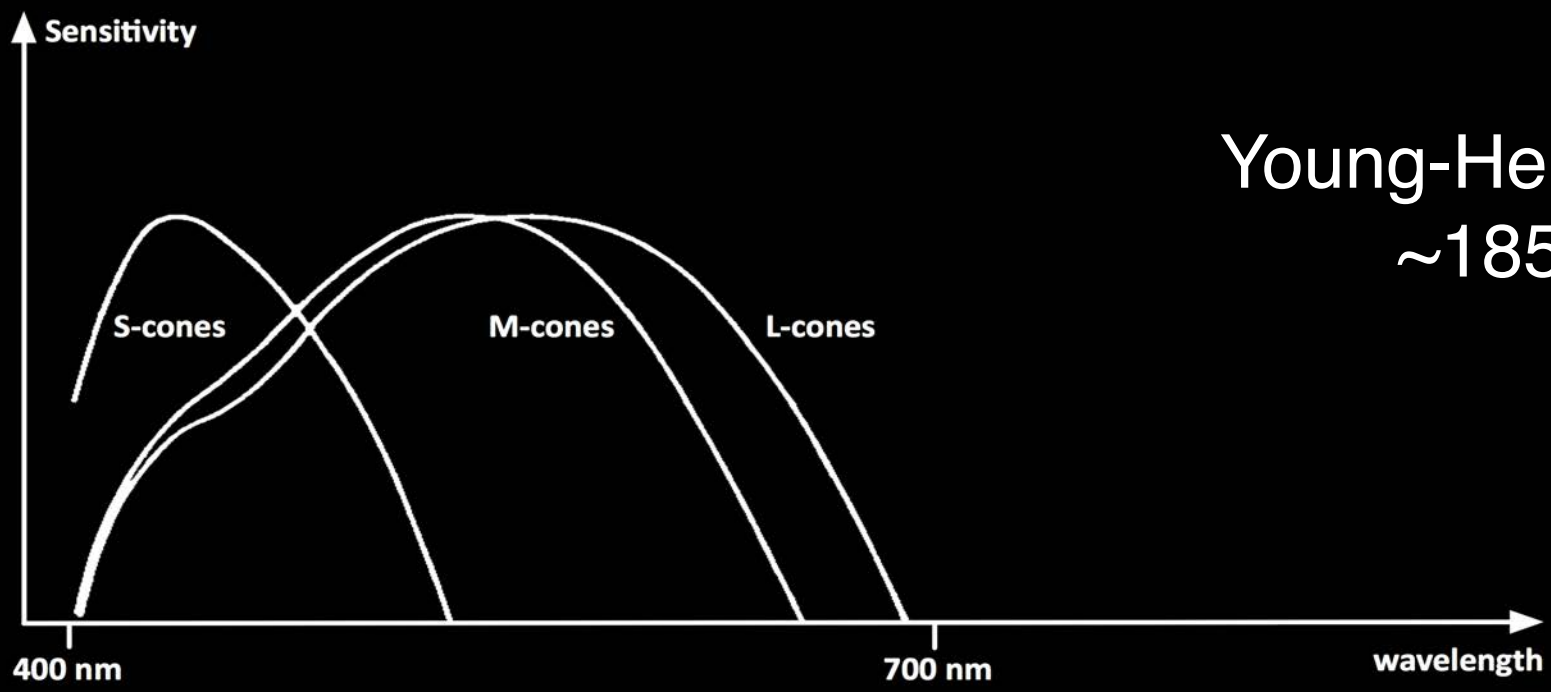
https://en.wikipedia.org/wiki/Theory_of_Colours

Newtonian World



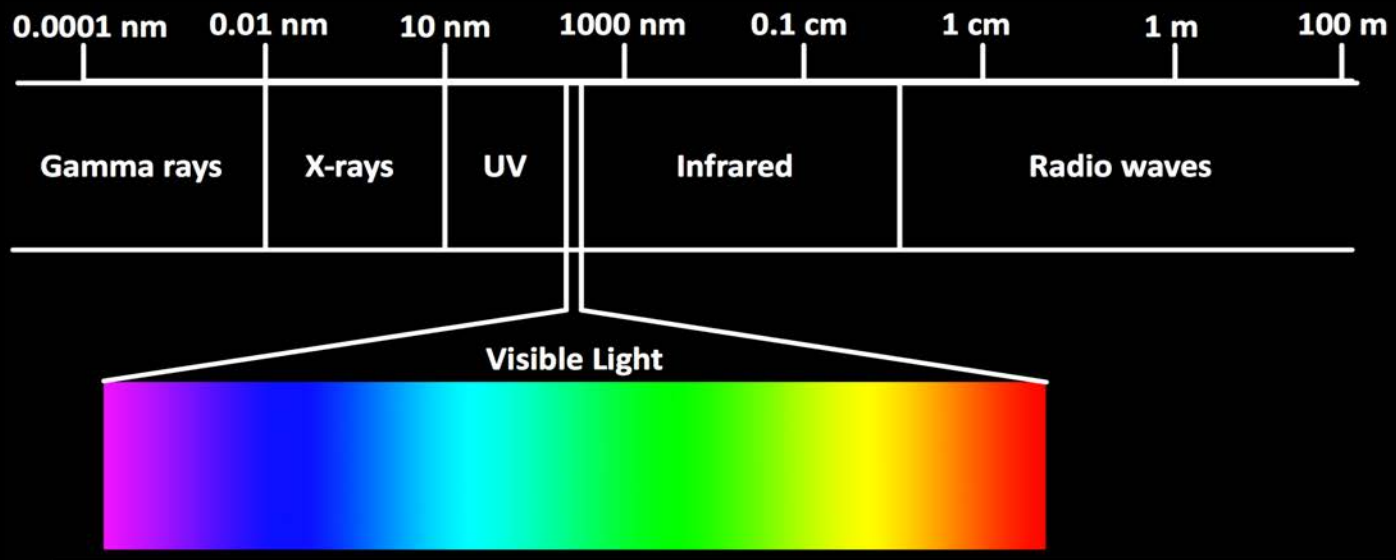
Trichromatic Color Vision





Young-Helmholtz
~1850

Additive Color Spaces/Encodings

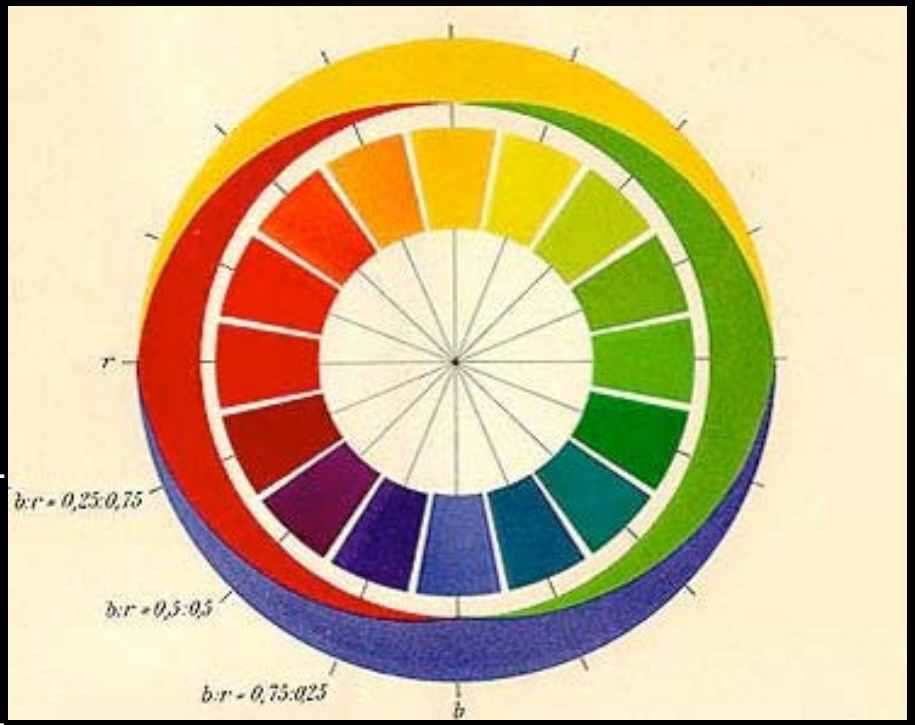


Visible (Red, Green, and Blue: RGB)

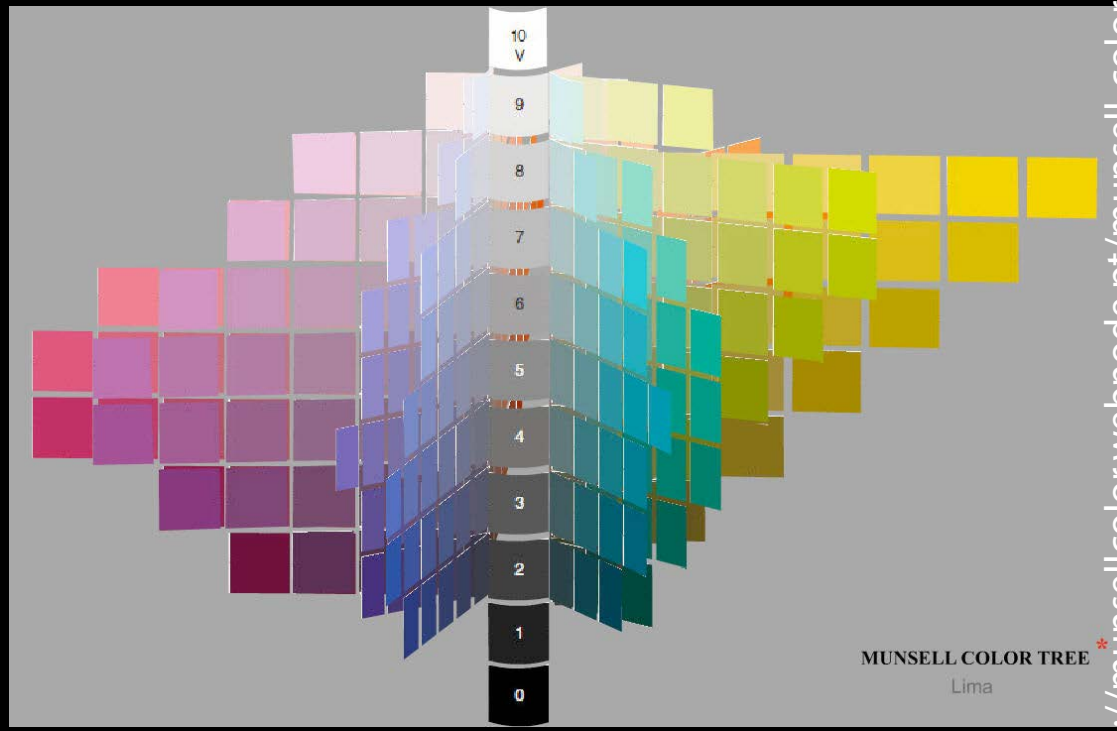
(s)RGB
XYZ
LMS

Opponent colors

- Better correlation with ***color appearance*** and ***color discrimination*** data.
  - Göthe 1810; Hering 1872; Munsell 1910, Jameson & Hurvich 1955, 1957.



Hering, 1872

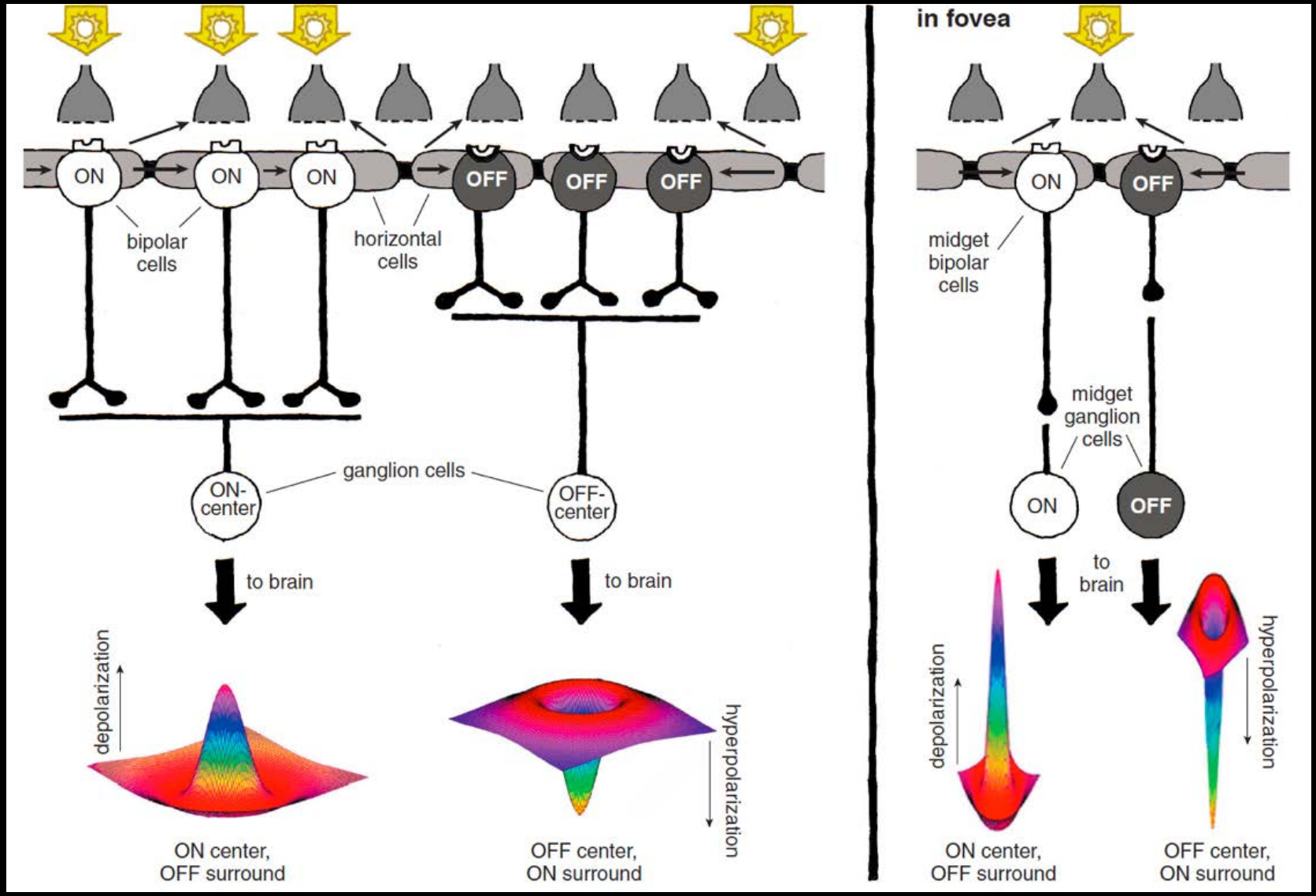


Munsell, 1920

http://www.handprint.com/HP/WCL/color2.html

http://munsellcolor.webnode.pt/munsell-color-tree/

Receptive Fields in the Retina

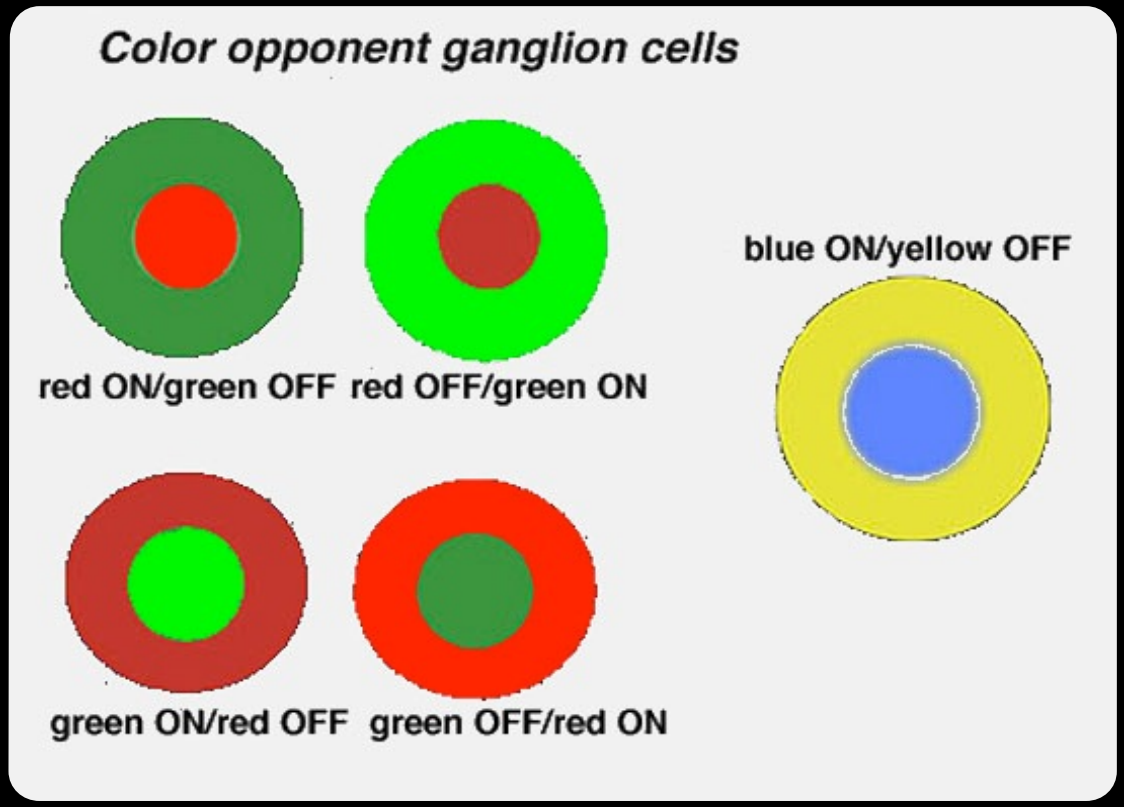


Kolb, 2003

R.L. DeValois, C.J. Smith, S.T. Kitai, and A.J. Karoly. Responses of single cells in different layers of the primate lateral geniculate nucleus to monochromatic light. *Science*, 127:238–239, 1958.

Opponent Colors

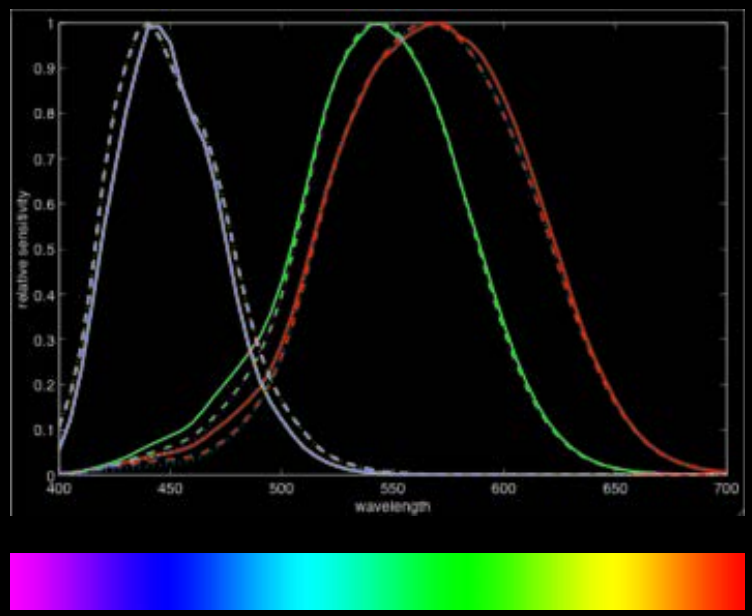
- Spectrally ***non-selective*** receptive fields: ***white-black***
- Spectrally ***selective*** receptive fields: ***red-green, blue-yellow***



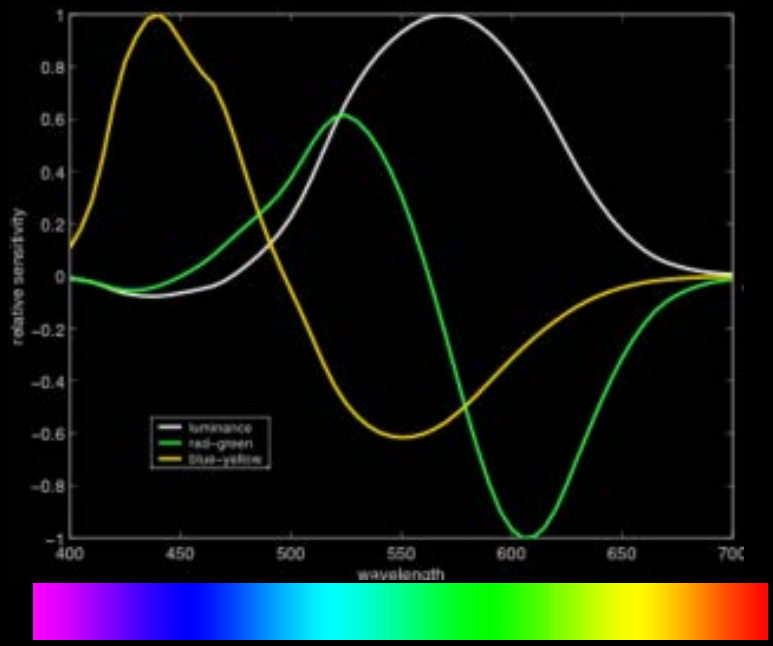
Luminance-chrominance

- ***Efficient*** encoding of L,M,S cone responses:
  - De-correlation of LMS cone responses result in opponent basis functions.

Stockman & Sharpe, 2002



PCA



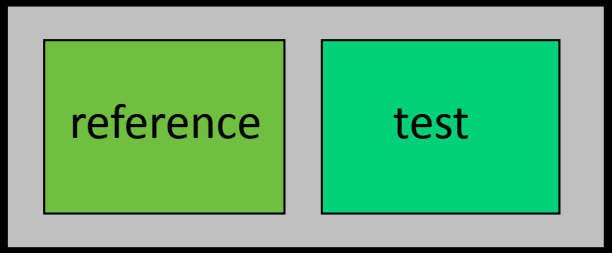
G. Buchsbaum and A. Gottschalk, Trichromacy, Opponent Colours Coding and Optimum Colour Information Transmission in the Retina. *Proc. of the Royal Society of London. Series B, Biological Sciences*, 1983.

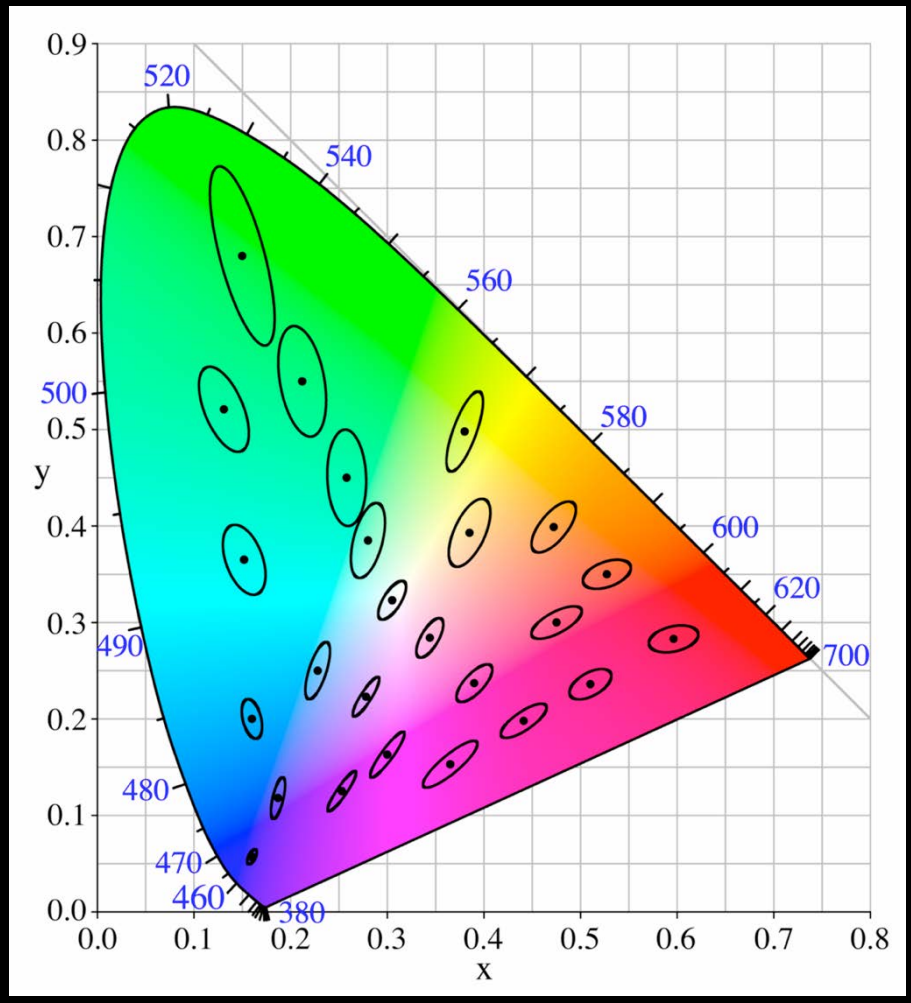
Opponent Color Spaces/Encoding

- Opponency works on ***cone contrast***, not on quantum catches of cones.
  - Different ways of modeling the contrast
    - Weber-type contrast
    - Log, gamma function, polynomial
- ***De-correlating*** transformation of cone fundamentals:
  - Luma (lightness, brightness, luminance) *f* [L'+M' (+S')]: αR' + βG' + γB'
  - Red-green *f* [L'-M']: αR' - βG' (+ γB')
  - Blue-yellow *f* [S' - (L'+M')]: γB' - (αR' + βG')
- ***Euclidian distances*** have some perceptual meaning.

CIELAB Color Space/Encoding

- An opponent color encoding based on the MacAdam ellipses*

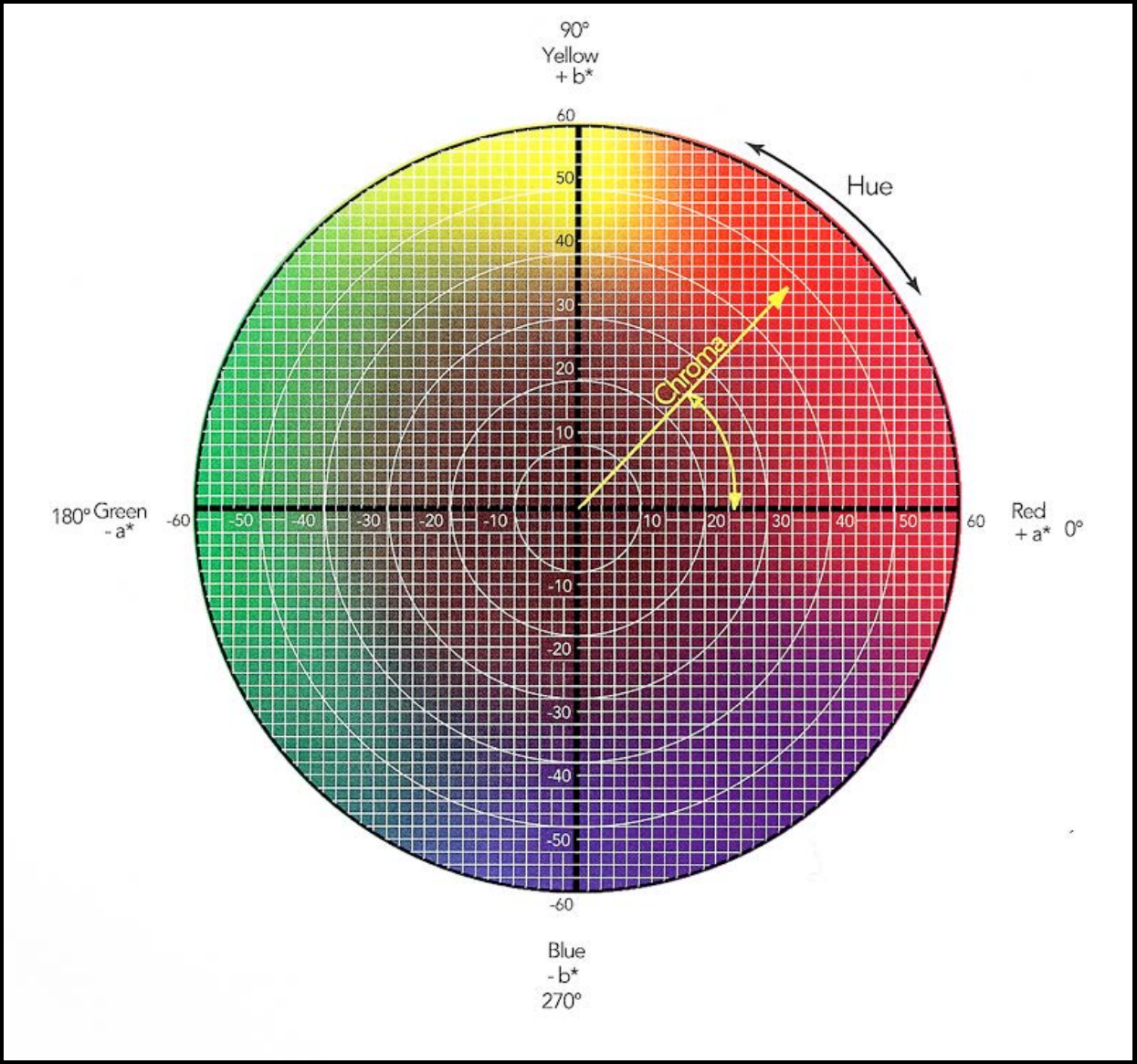




https://en.wikipedia.org/wiki/MacAdam_ellipse

*just noticeable differences of chromaticity

CIELAB Color Space



Perceptual Color Difference

$$\Delta E^*_{ab} = \left[(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2\right]^{1/2}$$

- Equal ΔE implies equally perceived color difference.

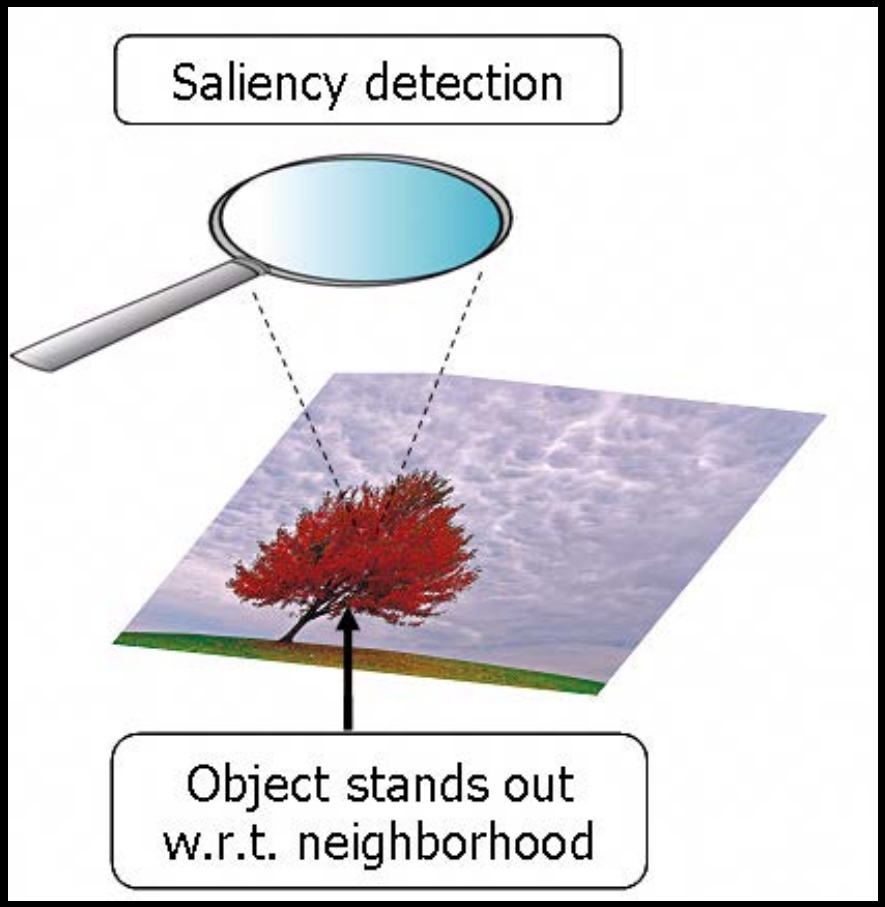
- $\Delta E^*_{ab} \sim 1$ is considered a good approximation of JND (Just noticeable difference) in simultaneous matching.

Salient Region Detection

Radhakrishna Achanta, Sheila Hemami, Francisco Estrada and Sabine Süsstrunk, Frequency-tuned Salient Region Detection, *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, 2009.

Salient regions...

- ...are the regions in the image that ***stand out*** (are visually conspicuous) with respect to the background.



Task-independent Saliency

Low-level vision, guides human visual attention

Task-specific Saliency

http://www.facedetection.com/facedetection/misc.htm

Task-specific Saliency

http://www.facedetection.com/facedetection/misc.htm

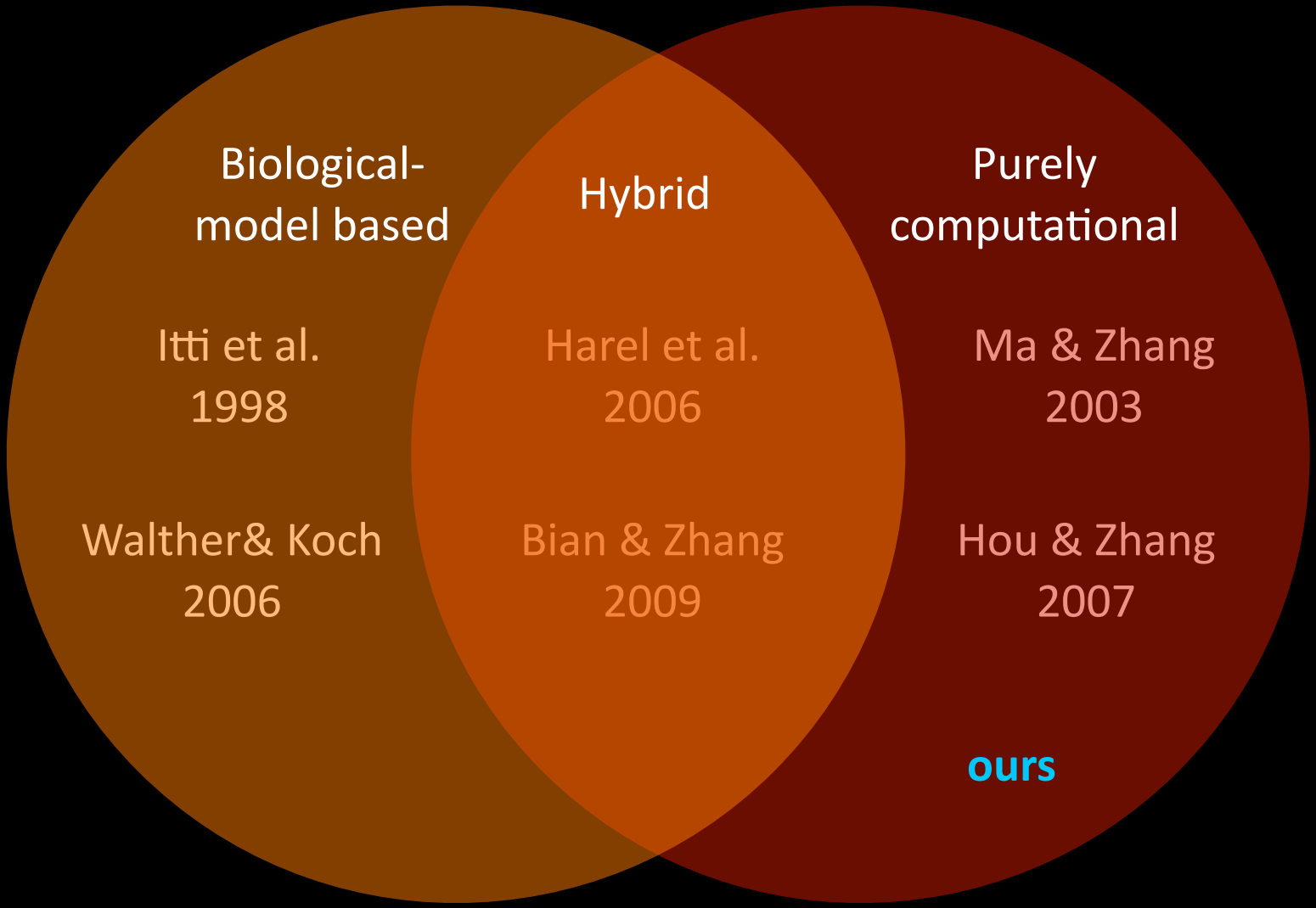
Object-detection

Salient region detector






Saliency Detectors



Center-surround contrast

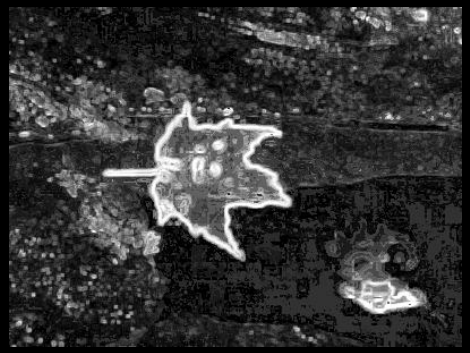
Salient Region Detectors

Input

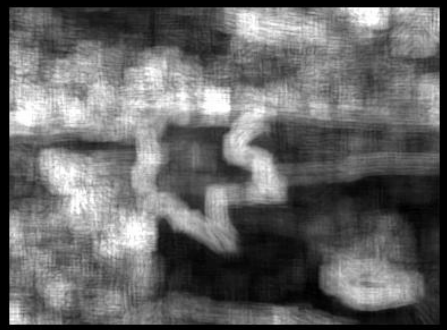
Itti et al.,IT98

Ma and Zhang, MA03

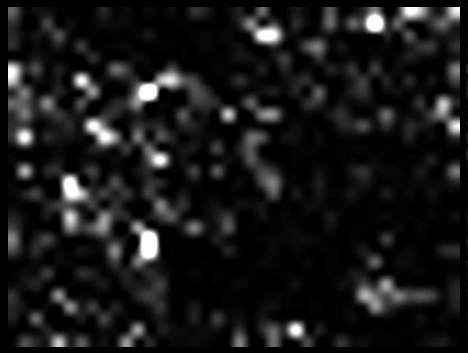
Harel et al.,GB06



Mancas et al., GR07

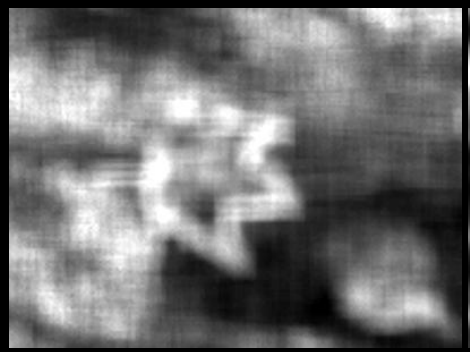


Bruce and Tsotsos, AIM07

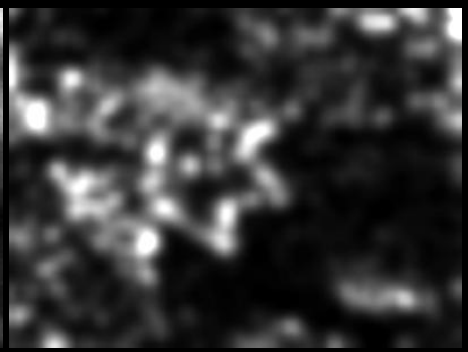


Hou and Zhang, SR07

Achanta et al., AC08



Zhang et al., SUN08



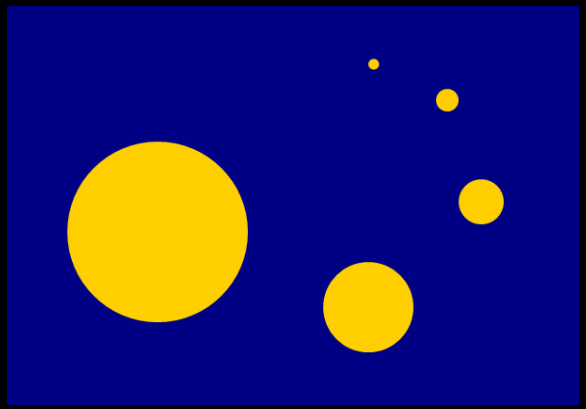
Bian and Zhang, SWQ09

FS-1

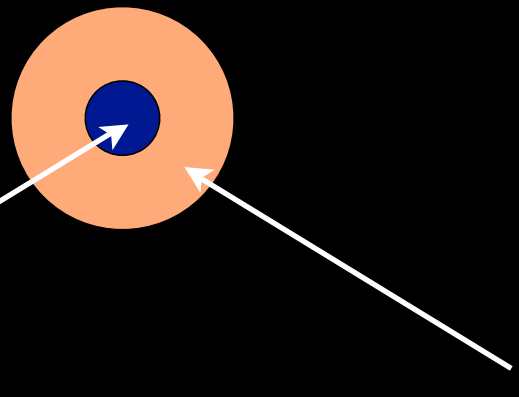
FS-2

What should a good detector do?

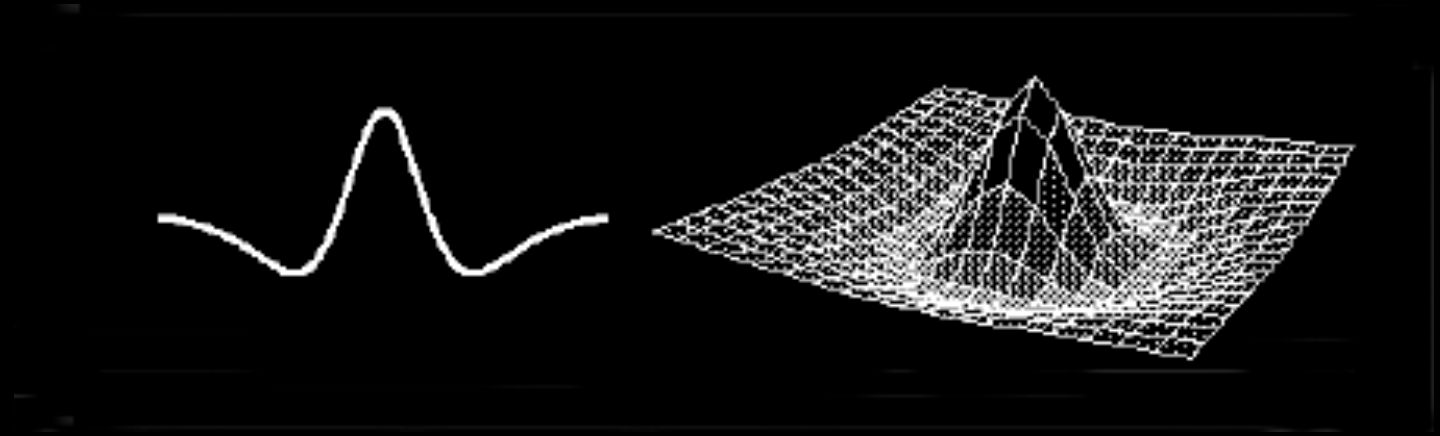
- Emphasize the largest salient objects in an image.
- Uniformly highlight whole salient regions.
- Establish well-defined boundaries of salient objects
- Disregard high frequencies arising from texture, noise and blocking artifacts.
- Efficiently output full resolution saliency maps.

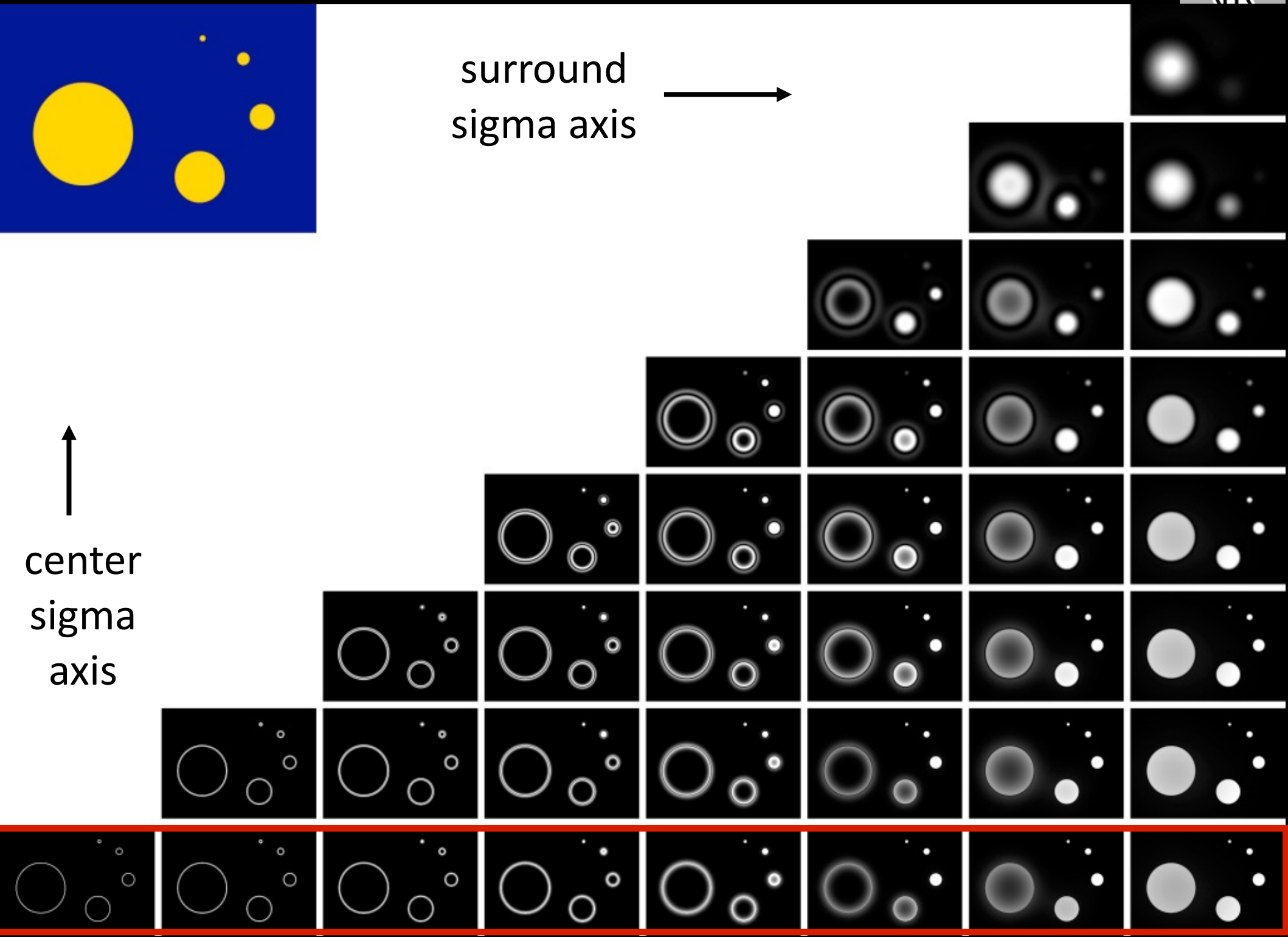


Saliency using Differences of Gaussians



Saliency = Abs [Center Gaussian - Surround Gaussian]




surround
sigma axis
center
sigma
axis

Algorithm

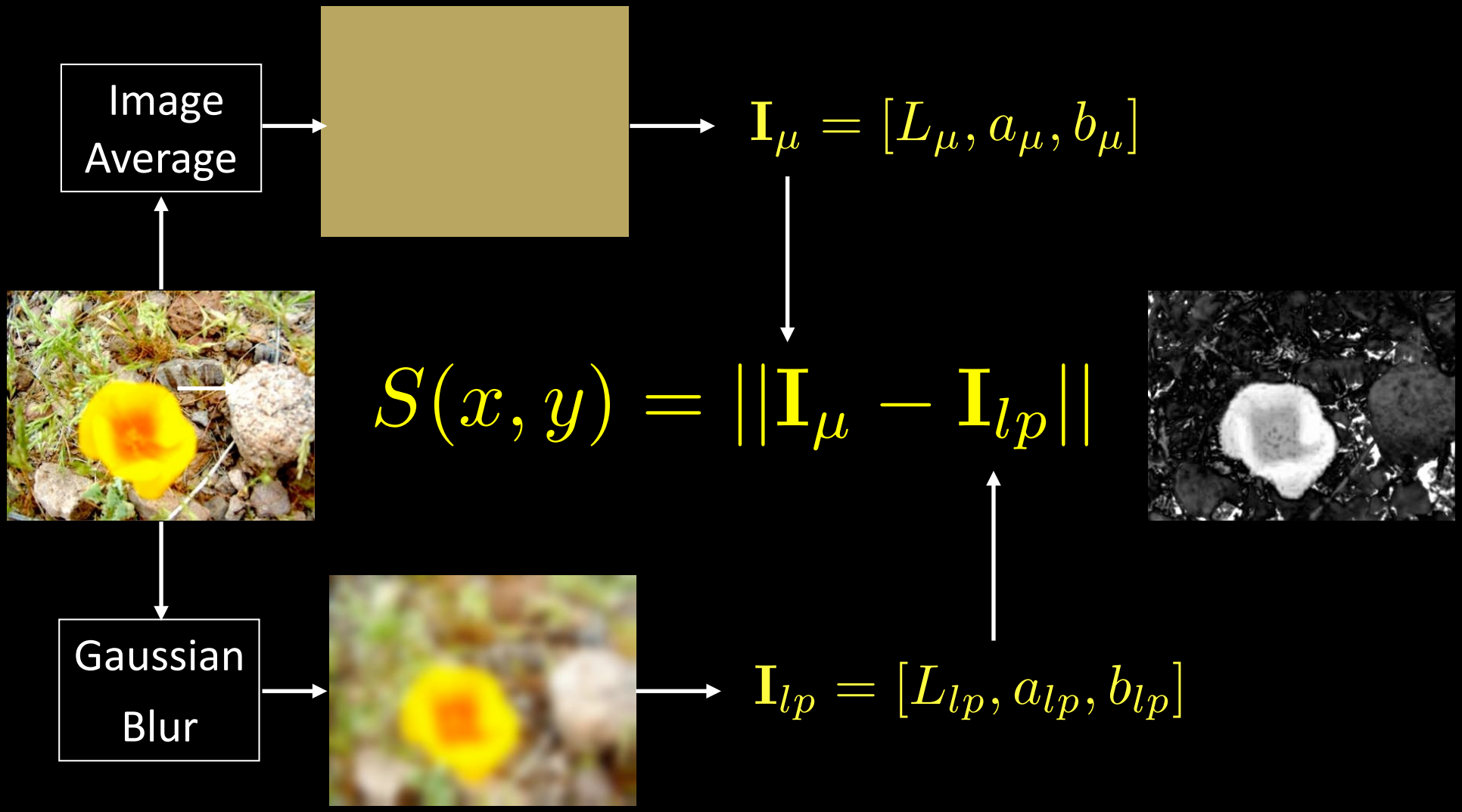
- Difference of Gaussian (DoG):

$$DoG(x,y) = \frac{1}{2\pi}\left[\frac{1}{\sigma_1^2}e^{-\frac{(x^2+y^2)}{2\sigma_1^2}} - \frac{1}{\sigma_2^2}e^{-\frac{(x^2+y^2)}{2\sigma_2^2}}\right]$$
$$= G(x,y,\sigma_1) - G(x,y,\sigma_2)$$

- ***Adding up DoGs:***

$$\sum_{n=0}^{N-1} G(x,y,\rho^{n+1}\sigma) - G(x,y,\rho^n\sigma)$$
$$= G(x,y,\rho^N\sigma) - G(x,y,\sigma)$$

Our Saliency Detection Algorithm



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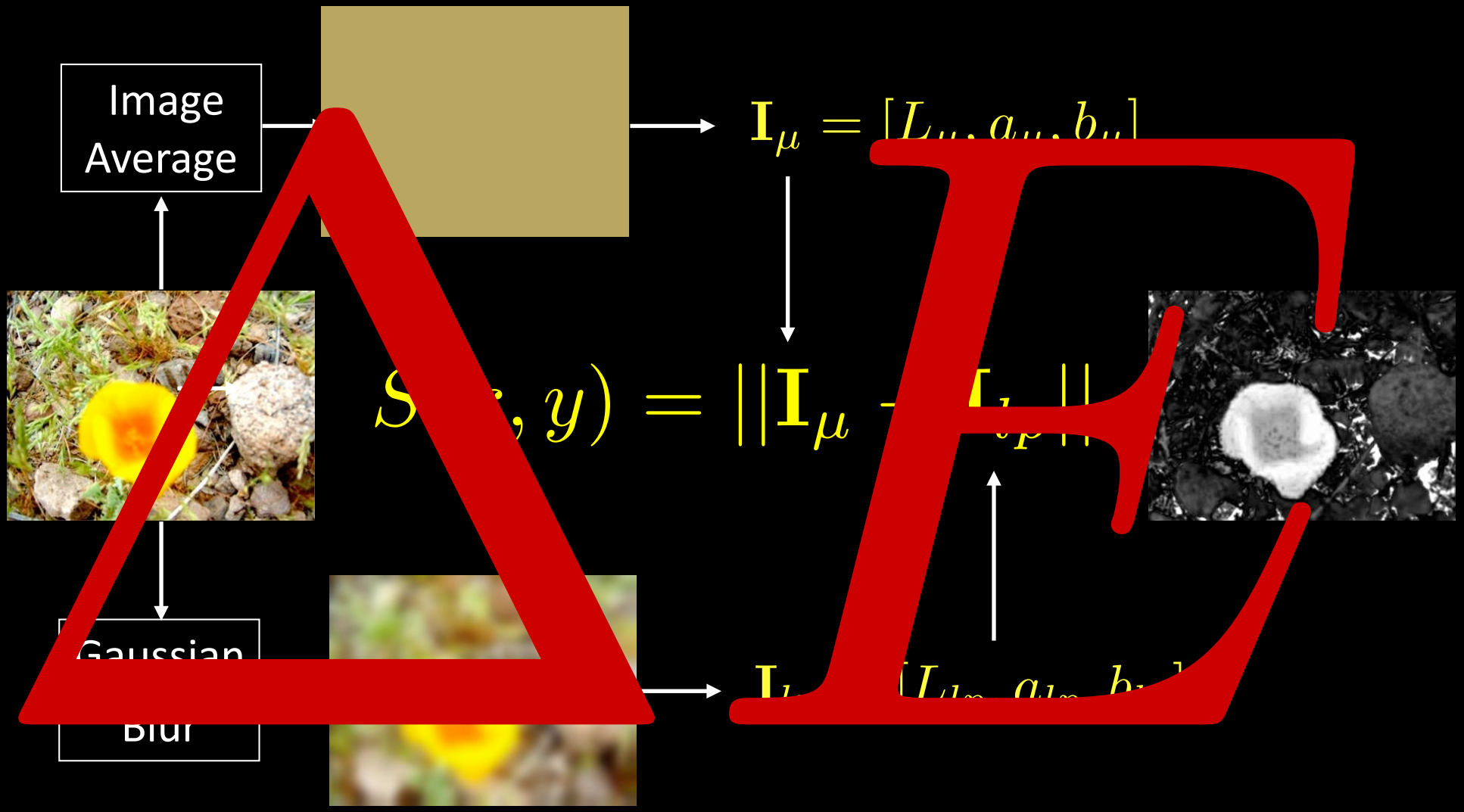


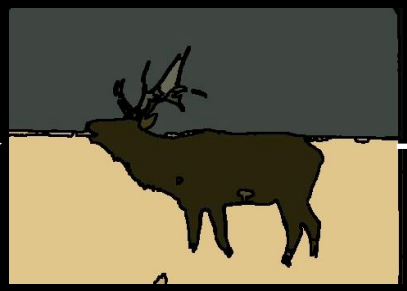
Image Segmentation

Input image

Compute saliency map

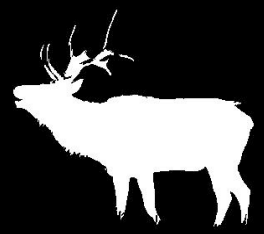
Compute average saliency for the image S_μ

Mean-shift segmentation

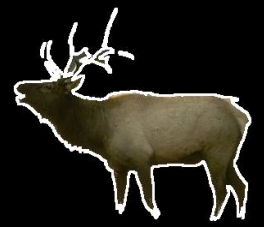


For any segment k, compute avg. saliency S_k

If $S_k > 2 \times S_\mu$ choose segment (binarize)



Extract object



Compare with ground truth!

Sample segmentation results

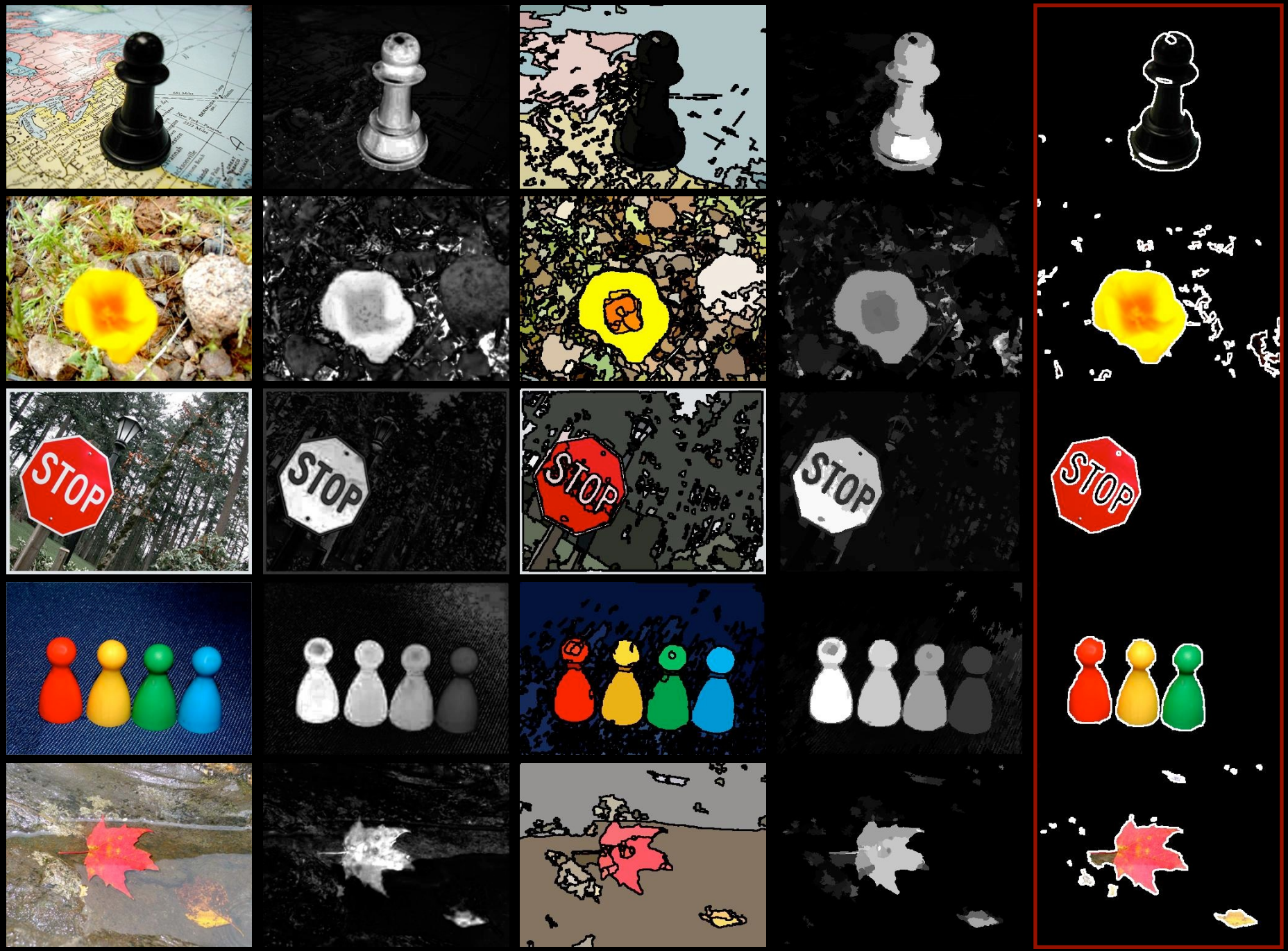
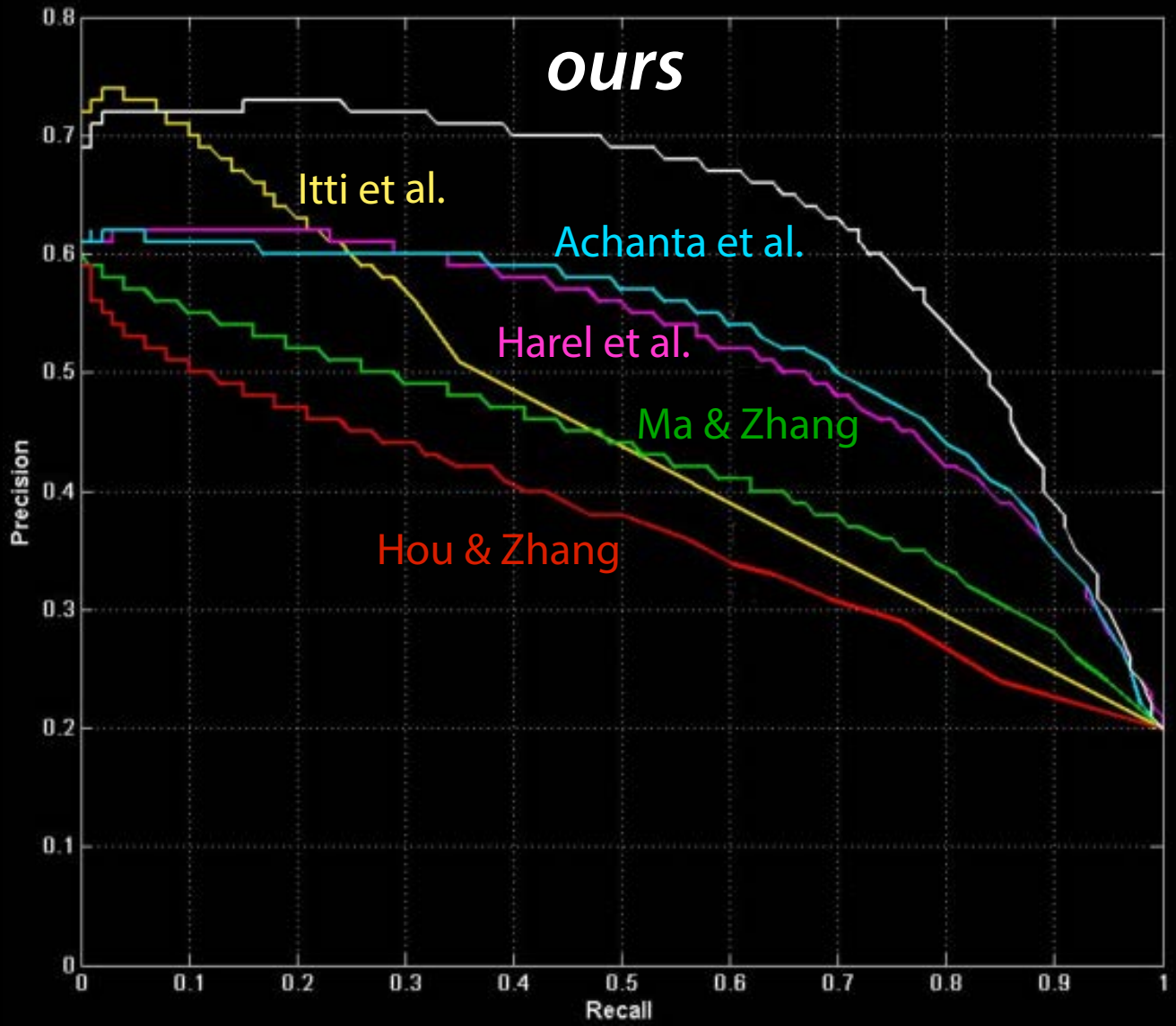
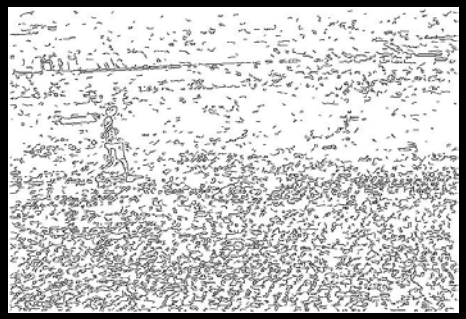


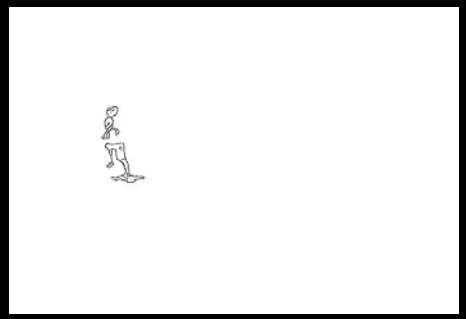
Image Segmentation Results



Based on an accurate object-bound ground truth of 1‘000 images

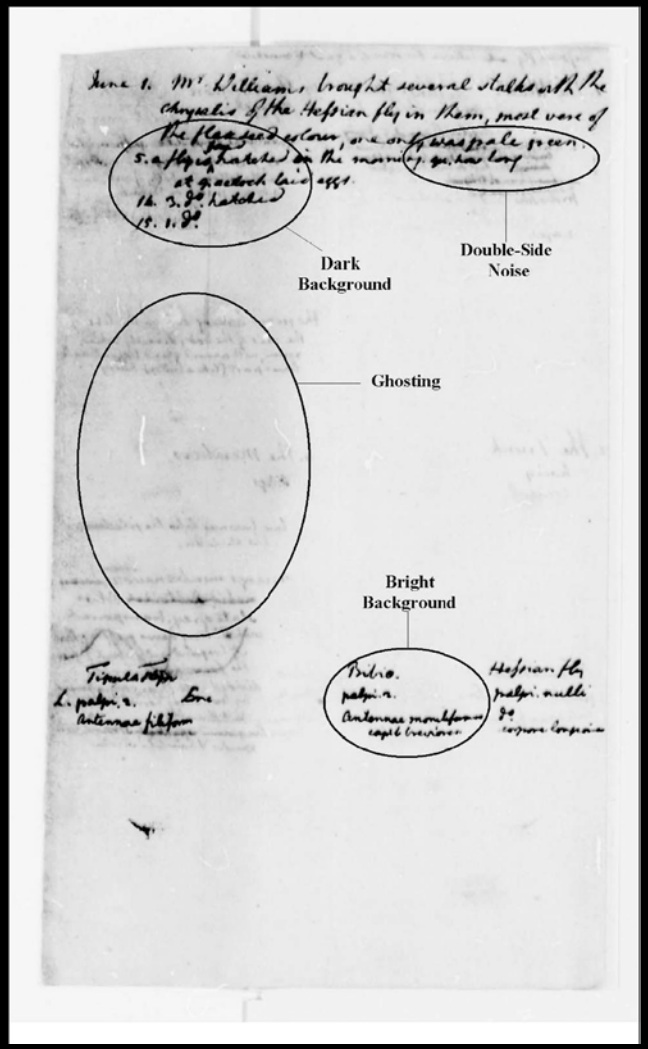
Improve Edge Detection

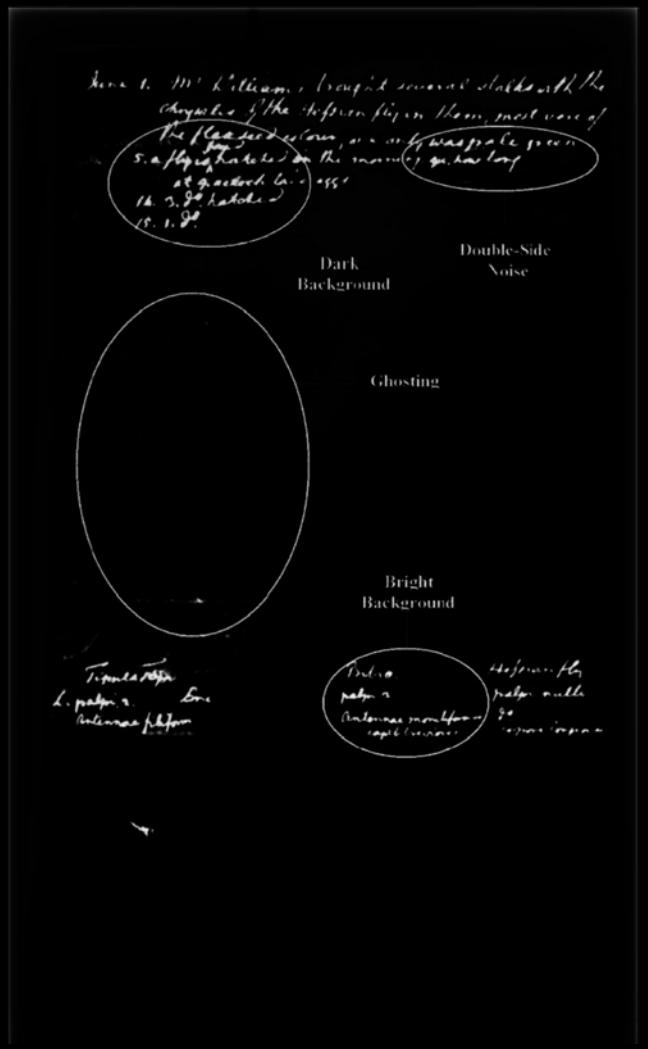



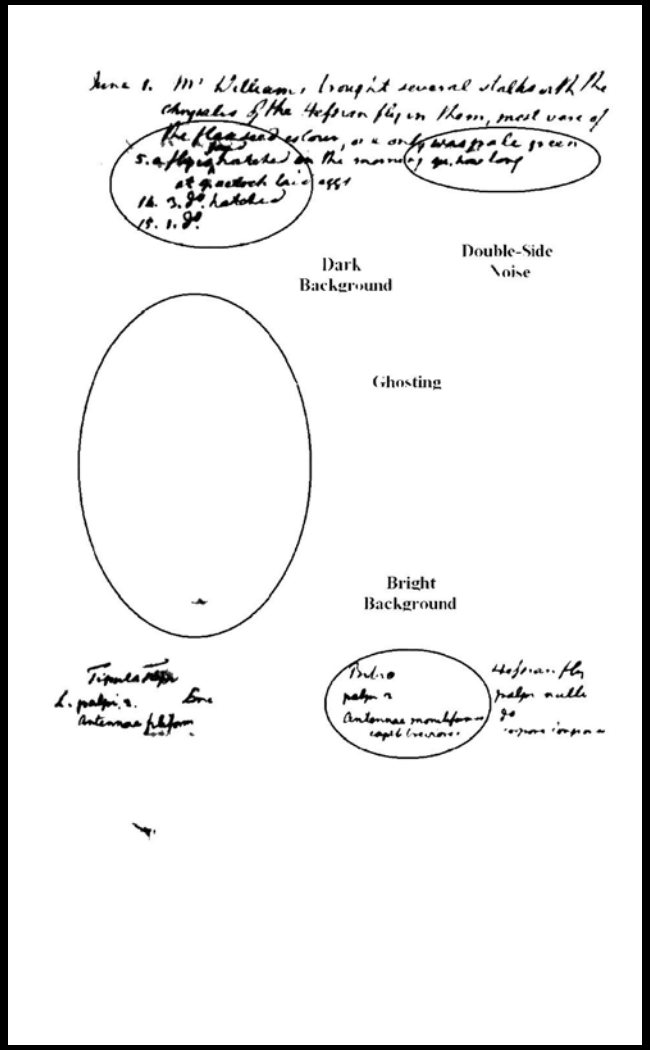




Document Correction

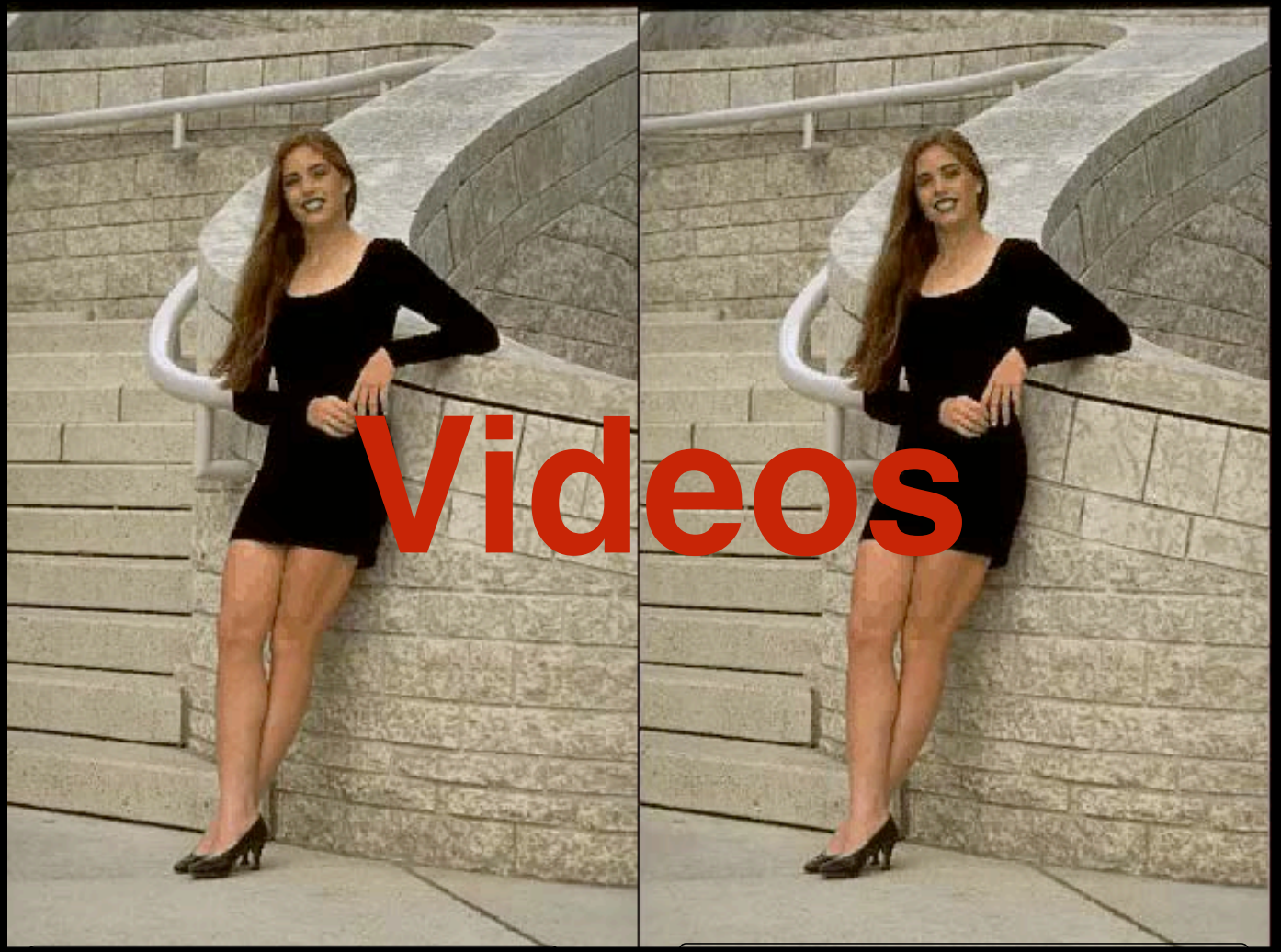






Combine low-level and task-specific Saliency

Image Resizing

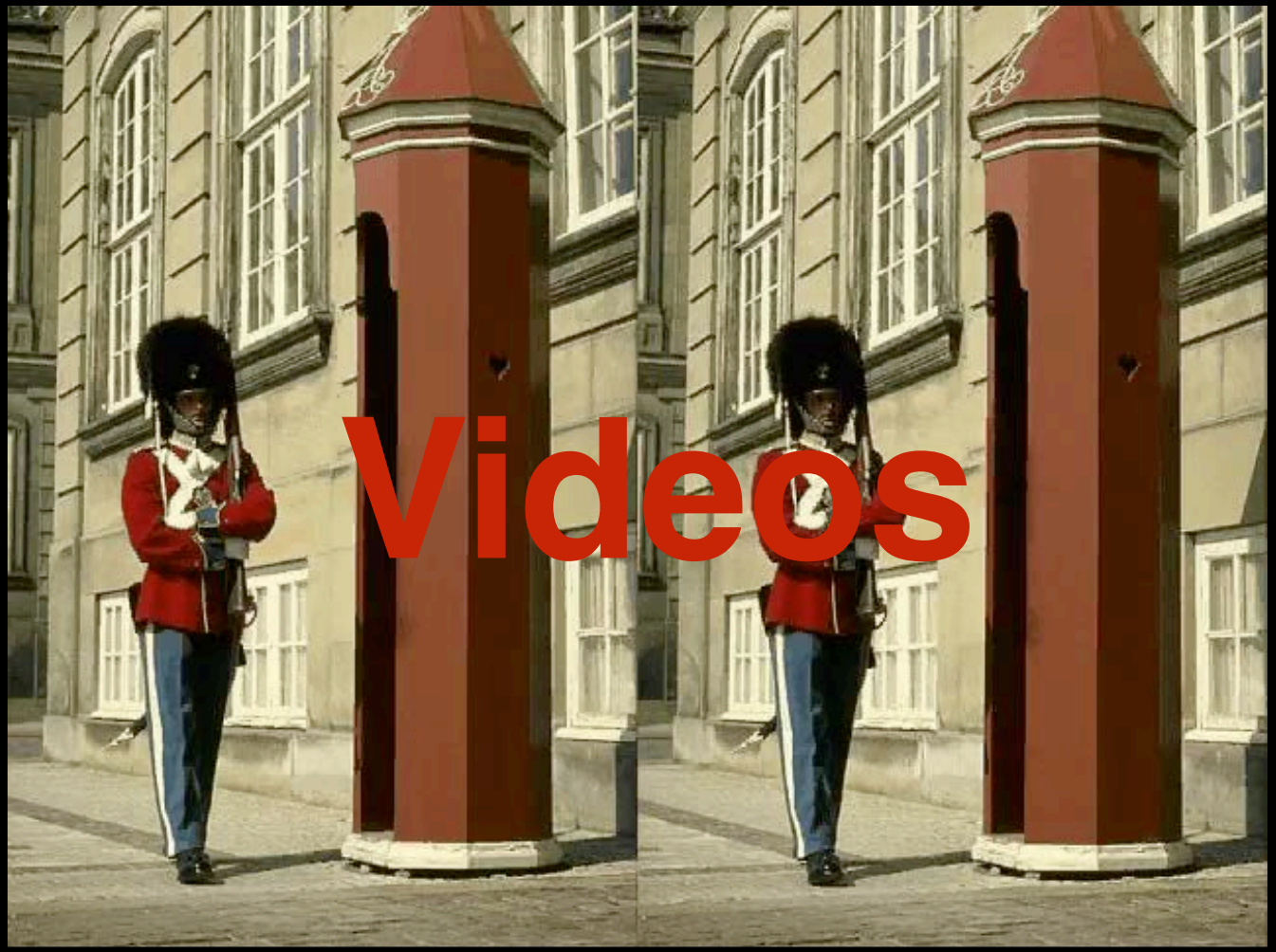


Original Seam carving

Seam carving with saliency

S. Avidan, and A. Shamir, Seam Carving for Content-Aware Image Resizing, *ACM SIGGRAPH,* 2007.
RK. Achanta and S. Süsstrunk, Saliency Detection for Content-aware Image Resizing, *IEEE ICIP,* 2009.

Comparisons



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RK. Achanta and S. Süsstrunk, Saliency Detection for Content-aware Image Resizing, *IEEE ICIP,* 2009.

Radhakrishna Achanta, Appu Shaji, Pascal Fua, and Sabine Süsstrunk, Image Summaries using Database Saliency, *ACM SIGGRAPH ASIA*, 2012.

Superpixels and Supervoxels

Radhakrishna Achanta, Appu Shaji, Kevin Smith, Aurelien Lucchi, Pascal Fua, and Sabine Süsstrunk, SLIC Superpixels Compared to State-of-the-Art Superpixel Methods, *IEEE Transaction of Pattern Analysis and Machine Intelligence,* 2012.

Superpixels

- Superpixels are pixel clusters of an over-segmented image.

State-of-the-Art

- ***Graph based algorithms***
  - [GS04] Efficient graph based segmentation [Felzenszwalb and Huttenlocher, IJCV 2004]
  - [NC05] Normalized cuts [Mori, ICCV 2005]
  - [SL08] Superpixel lattice [Moore et al. CVPR 2008]
  - [GC10] Graph cuts [Veksler et al. ECCV 2010]
- ***Gradient based algorithms***
  - [WS91] Watershed [Vincent and Soille, PAMI 1991]
  - [MS02] Mean shift [Comaniciu and Meer, PAMI 2002]
  - [TP09] Quick shift [Vedaldi and Soatto, ECCV 2008]
  - [QS09] Turbopixels [Levinstein et al. PAMI 2009]

State-of-the-Art

Input

Felzenszwalb and Huttenlocher

GS04

G. Mori

NC05

Vedaldi and Soatto

QS09

Levinstein et al.

TP09

SLIC

Good boundary adherence but no control over the number of superpixels

Input

Felzenszwalb and Huttenlocher

GS04

G. Mori

NC05

Vedaldi and Soatto

QS09

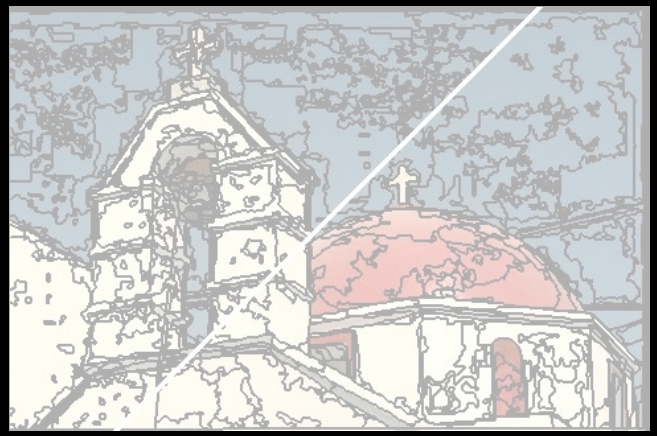
Levinstein et al.

TP09

SLIC

Control over the number of superpixels but poor boundary adherence

Input



Felzenszwalb and Huttenlocher

GS04

G. Mori

NC05

Vedaldi and Soatto

QS09

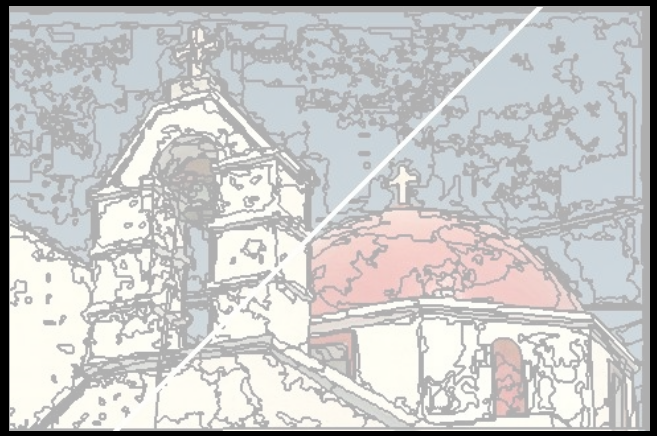
Levinstein et al.

TP09

SLIC

Control ***and*** good boundary adherence

Input



Felzenszwalb and Huttenlocher

GS04

G. Mori

NC05

Vedaldi and Soatto

QS09

Levinstein et al.

TP09

SLIC

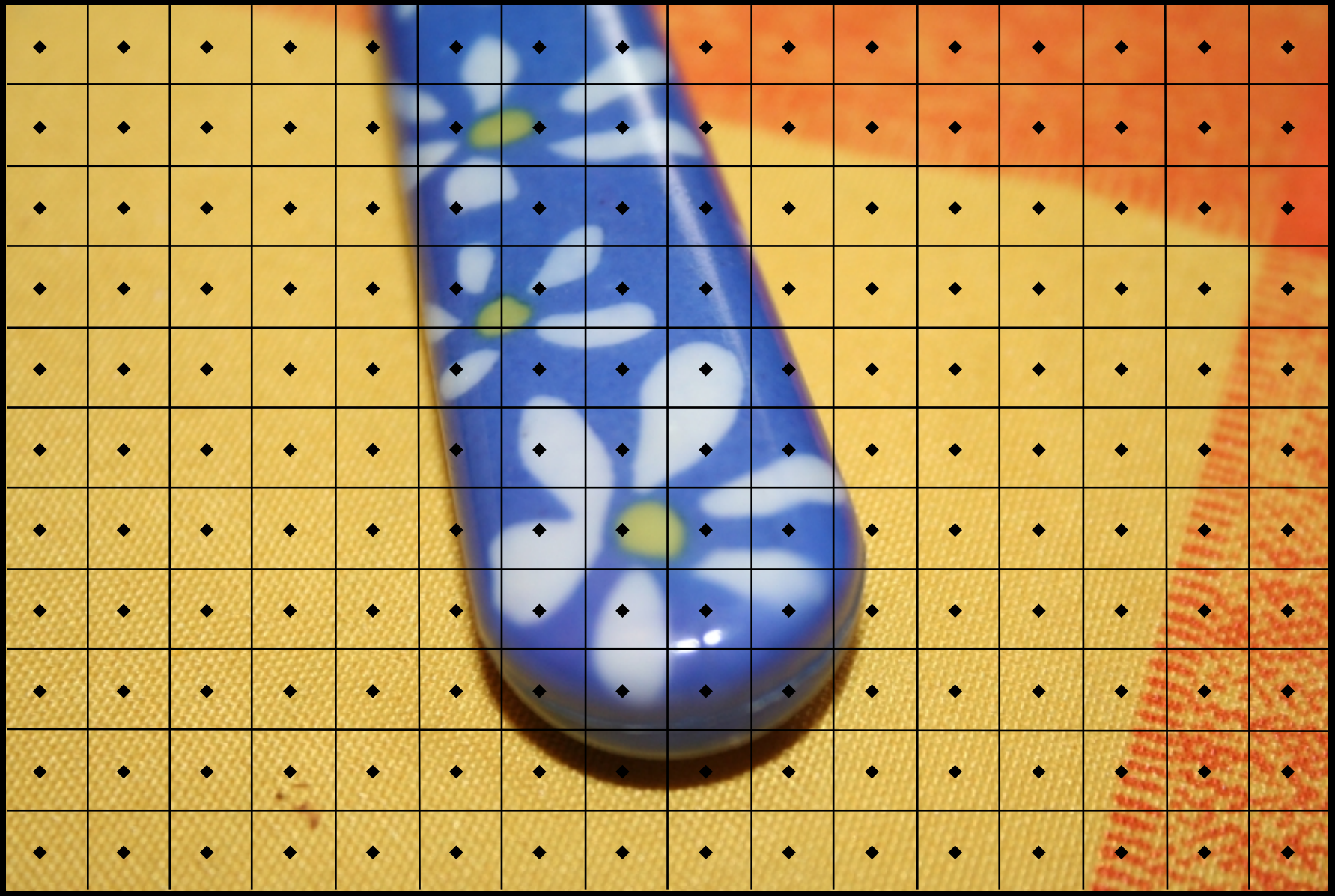
SLIC Superpixel/voxel Algorithm

- ***SLIC: Simple linear iterative clustering***
- *k*-means in 3-6D space of color value and spatial coordinates.
- Normalize color and spatial distances using maximum distances within a cluster.

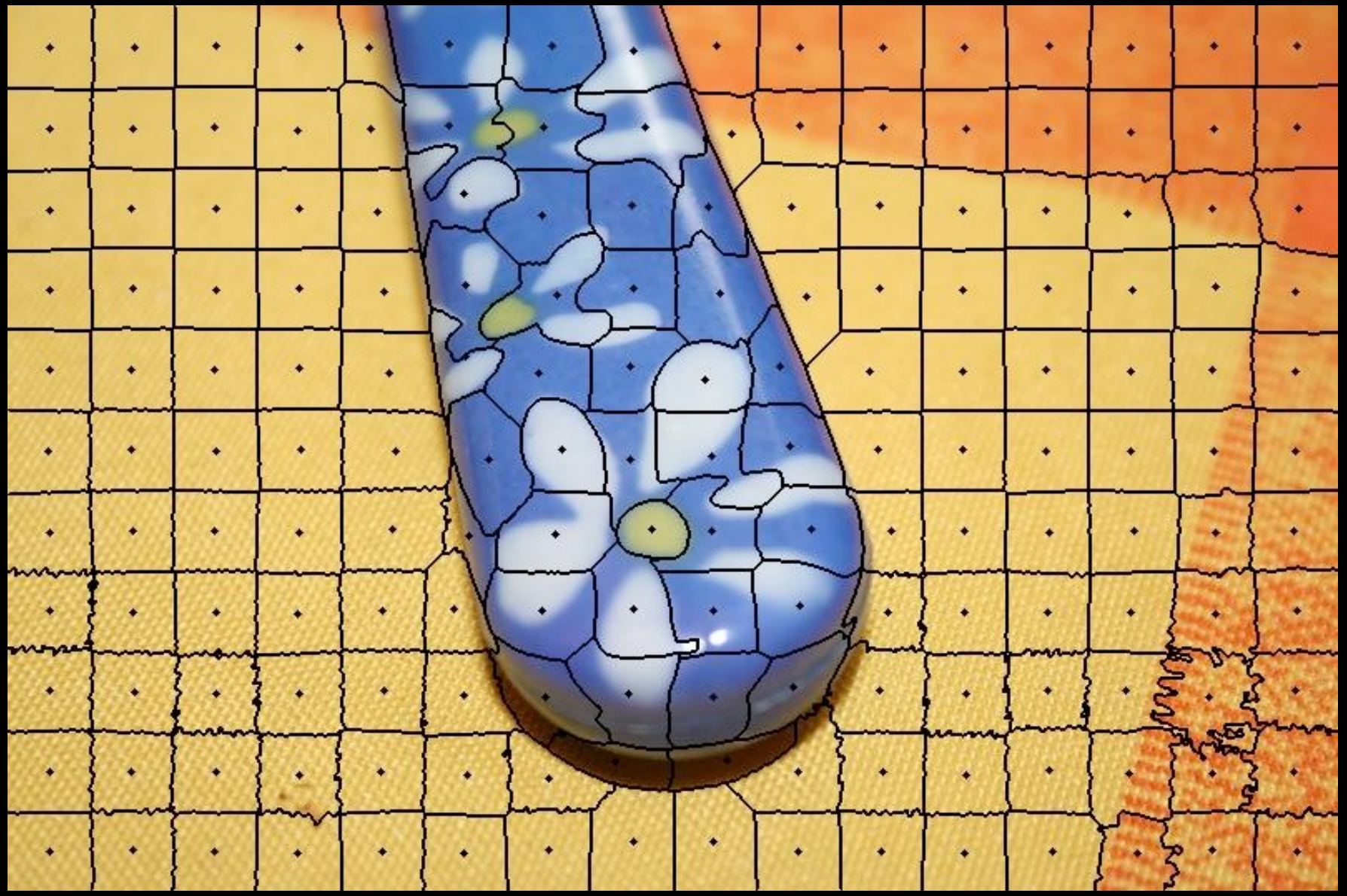
$$D = \sqrt{\frac{1}{S}[(x_j - x_i)^2 + (y_j - y_i)^2 + (z_j - z_i)^2] + \frac{1}{m}[(L_j - L_i)^2 + (a_j - a_i)^2 + (b_j - b_i)^2]}$$

Spatial proximity term CIELAB proximity term

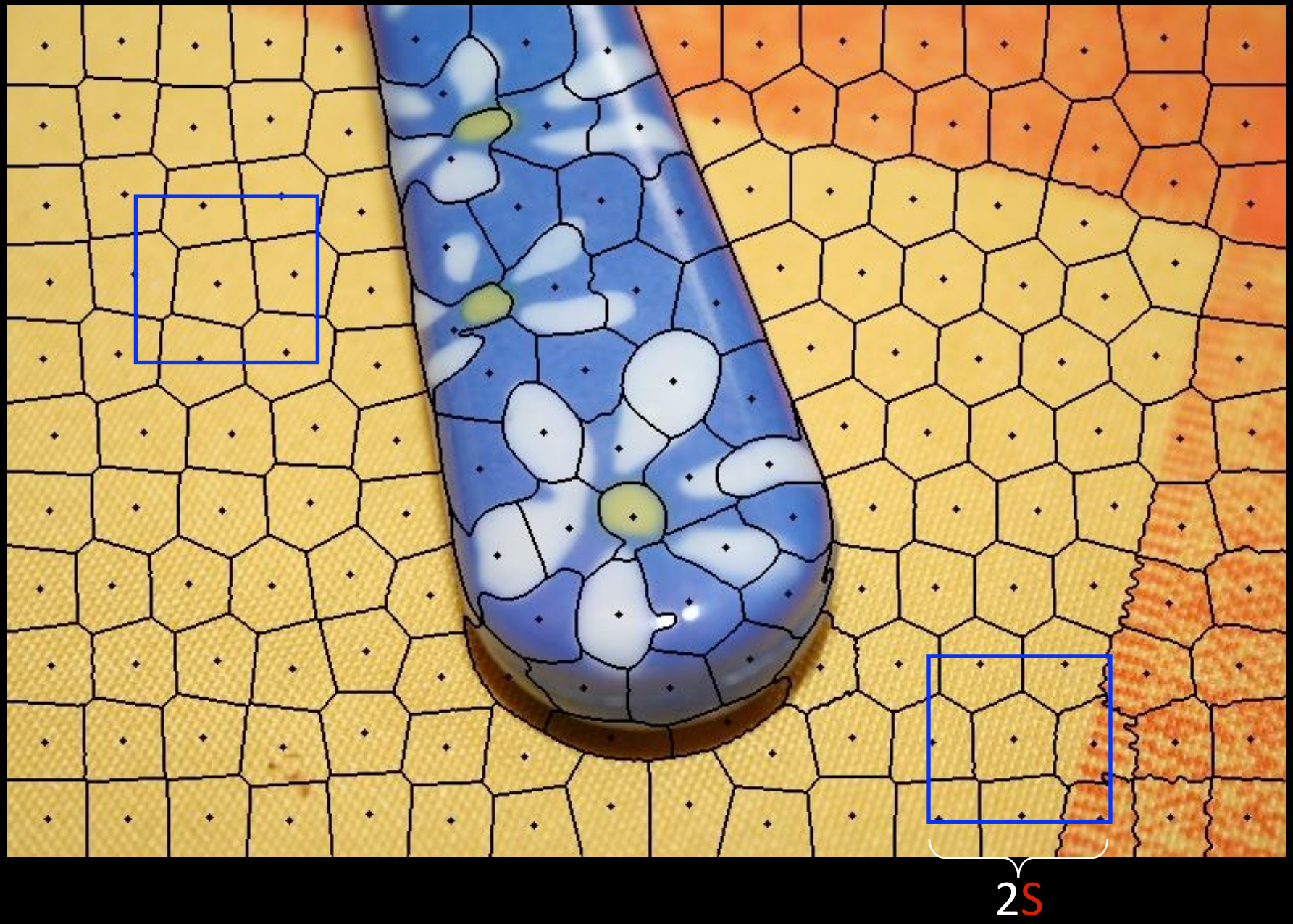
Choose *k* seeds at steps S



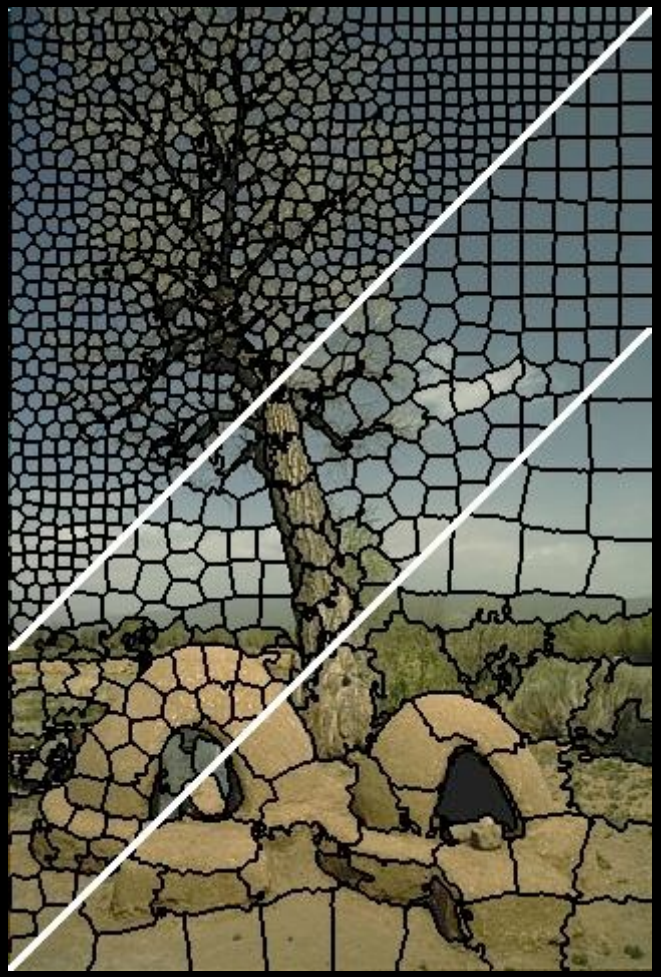
After 1 iteration

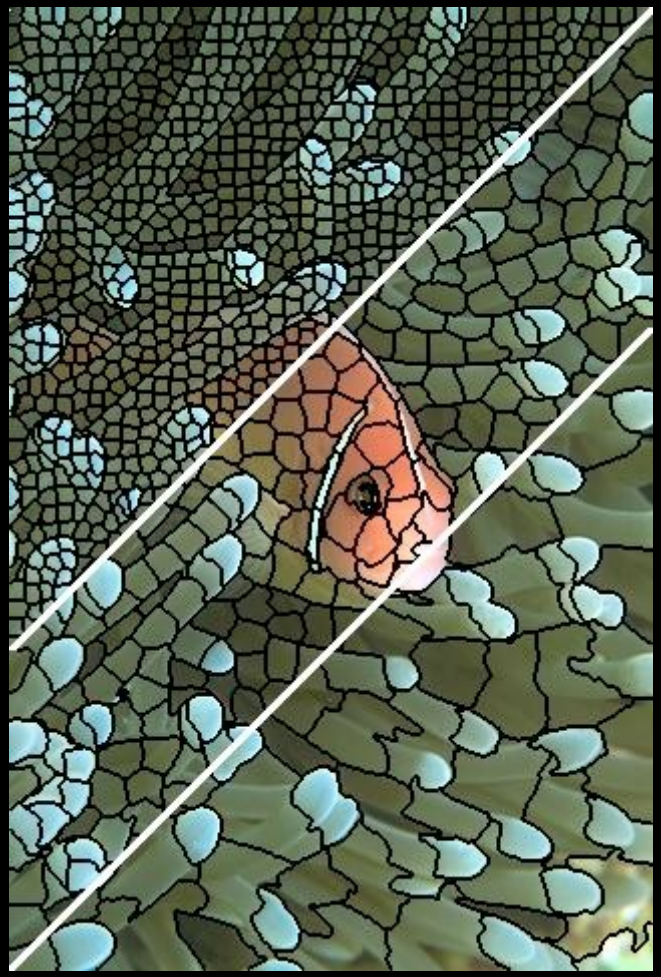


After 10 iterations



Results





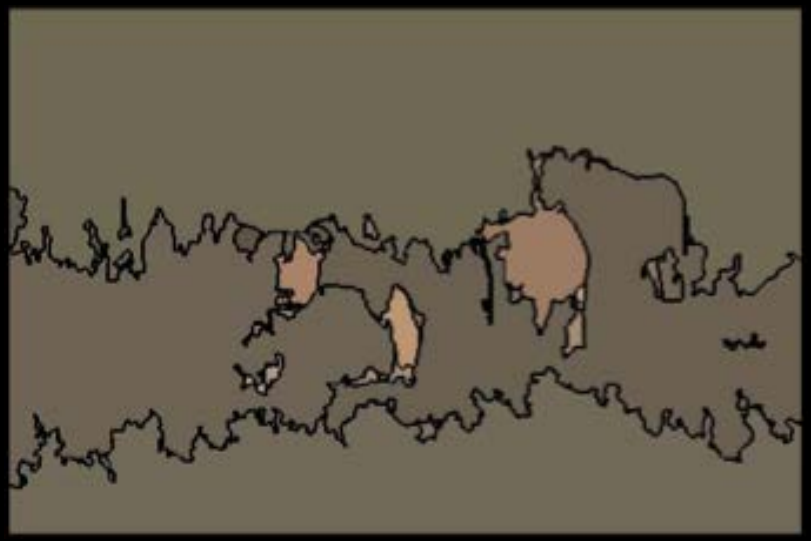
Object class recognition

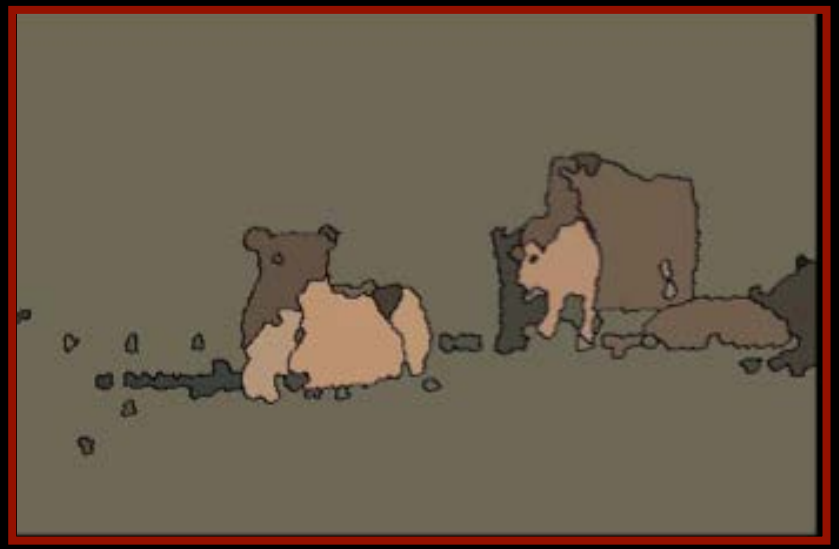
Gould et al., IJCV 2008, STAIR Vision Library

	GS04	NC05	TP09	QS09	**SLIC**
Classification accuracy	74.6%	75.9%	75.1%	62.0%	**76.9%**

Compared to NC05, SLIC is 400 times faster.

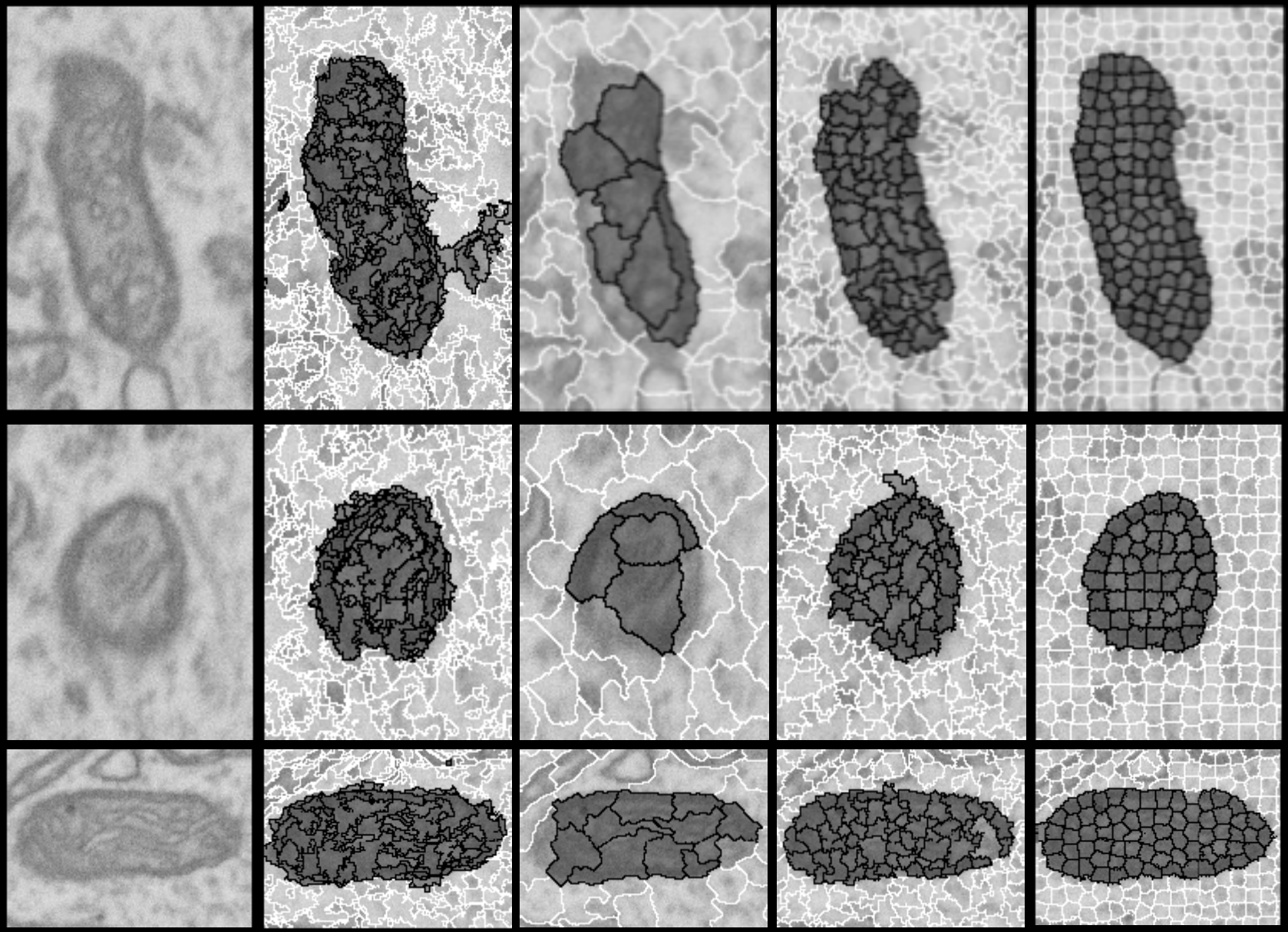
Superpixel Graph-based Segmentation



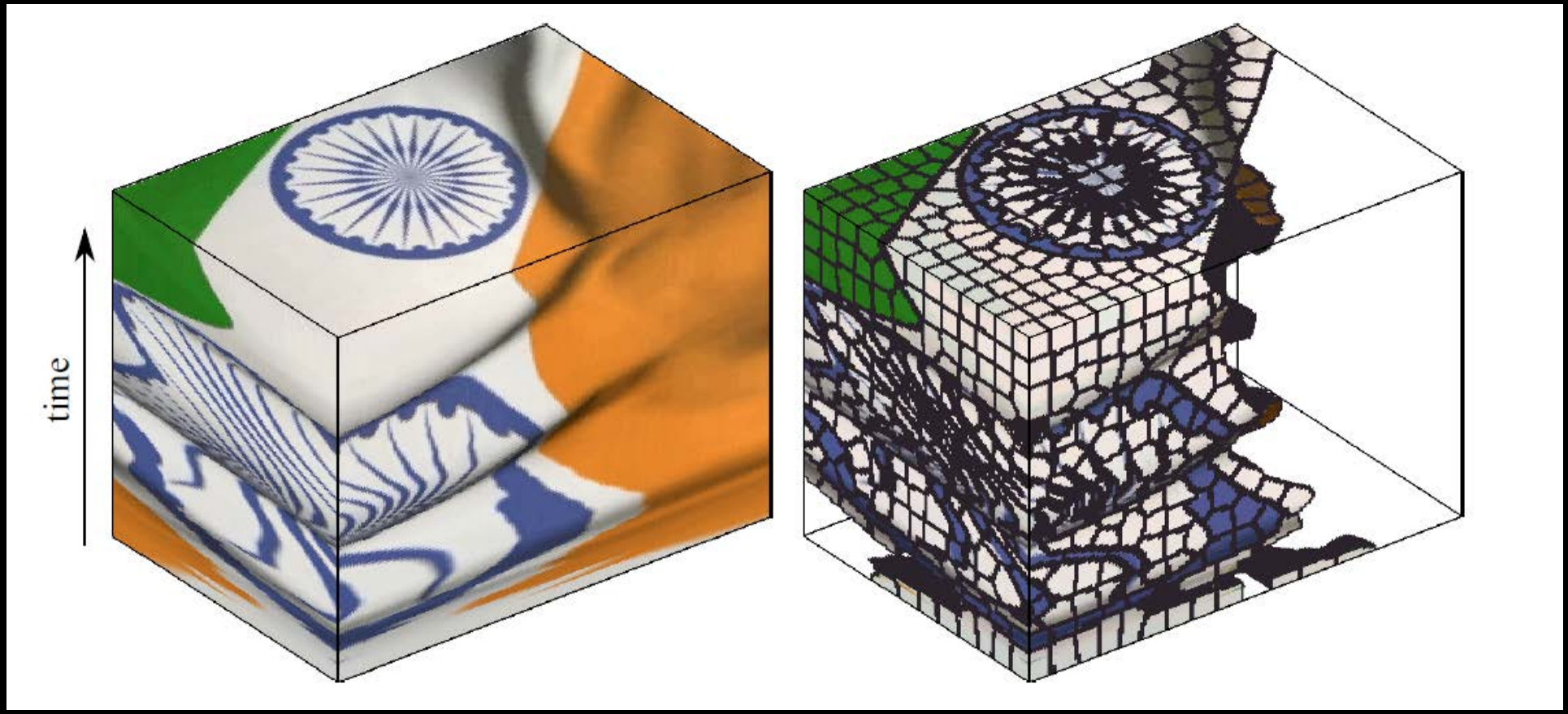


Our result

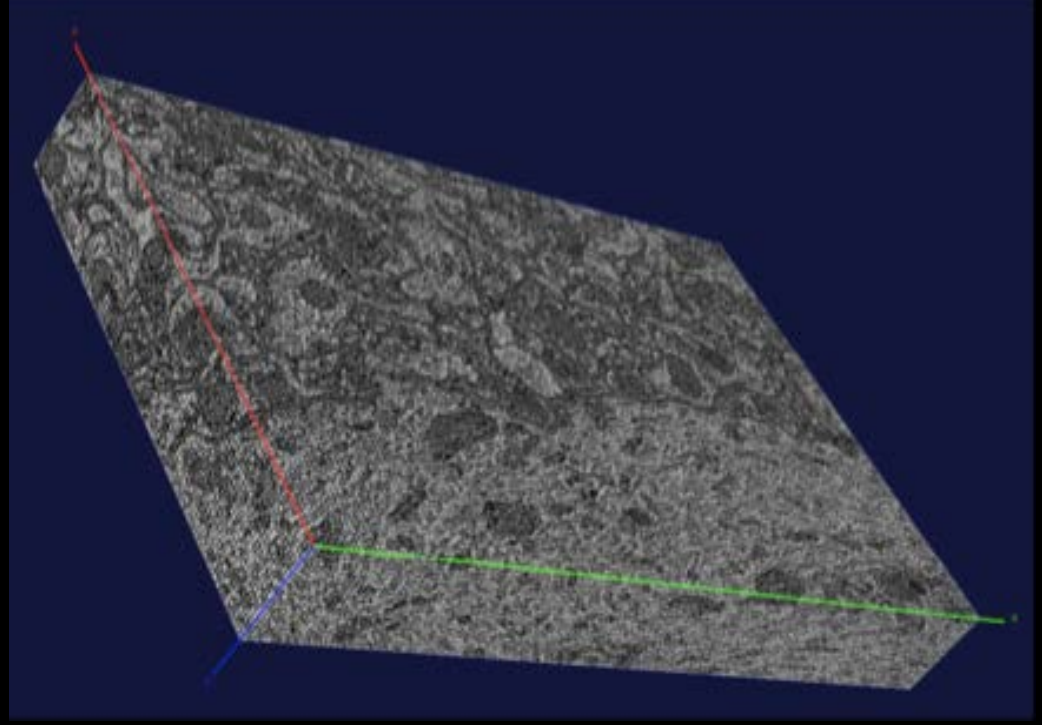
Mitochondria Detection

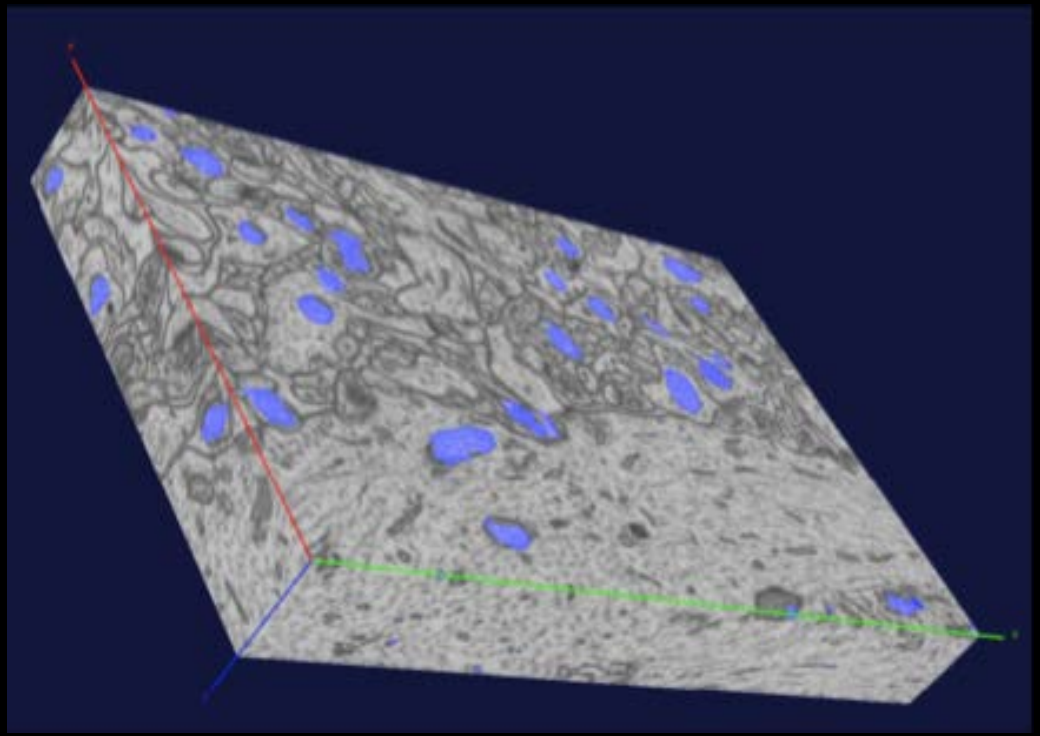


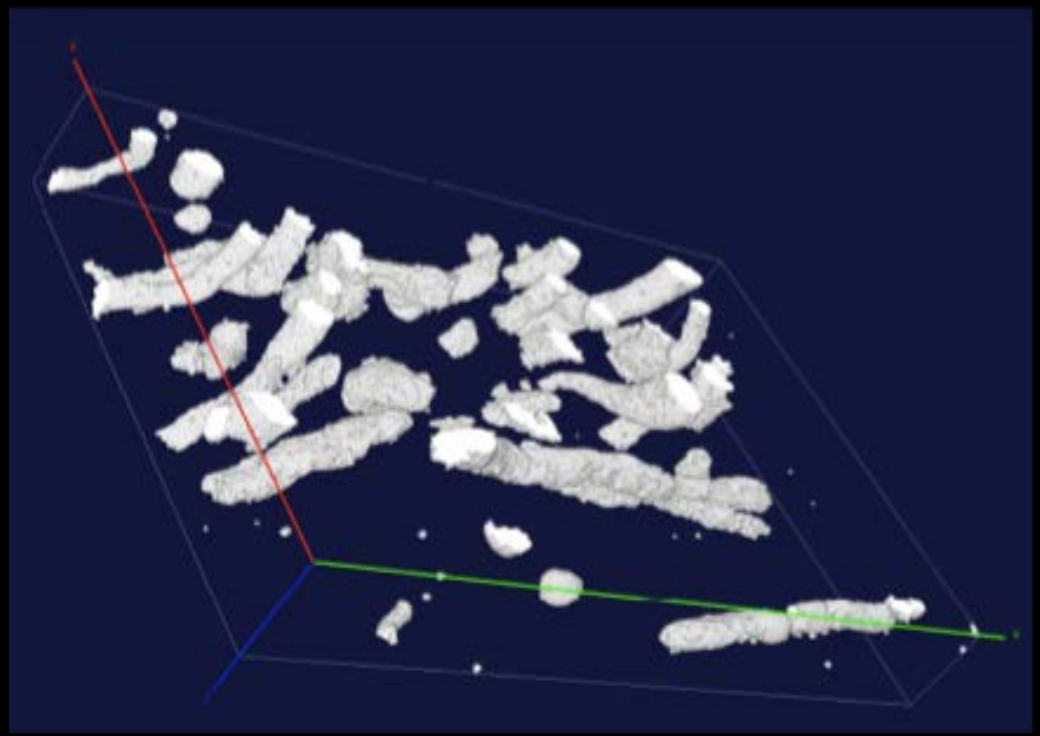
Supervoxels



Gökhan Yildirim, Appu Shaji, and Sabine Süsstrunk, Estimating Beauty Ratings of Videos using Supervoxels *ACM Multimedia,* 2013.





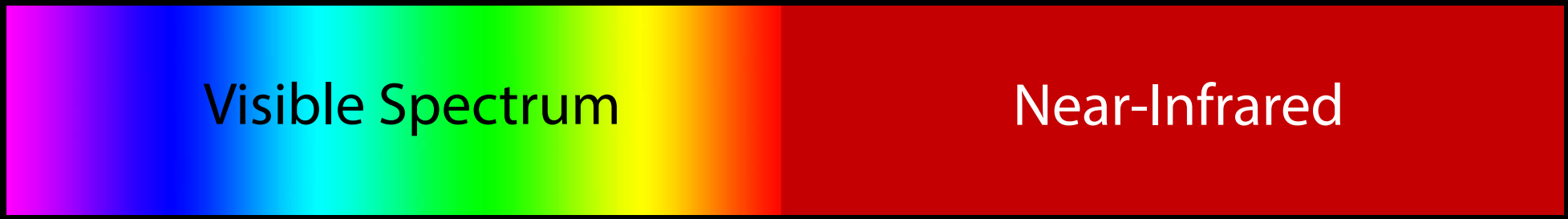


A Lucchi, K Smith, R Achanta, G Knott, P Fua, Supervoxel-based segmentation of mitochondria in EM image stacks with learned shape features, *IEEE Transactions on Medical Imaging,* 2012.

"Opponency" and Near-Infrared

M. Brown and S. Süsstrunk, Multispectral SIFT for Scene Category Recognition, Proc. *IEEE International Conference on Computer Vision and Pattern Recognition* (CVPR), 2011.

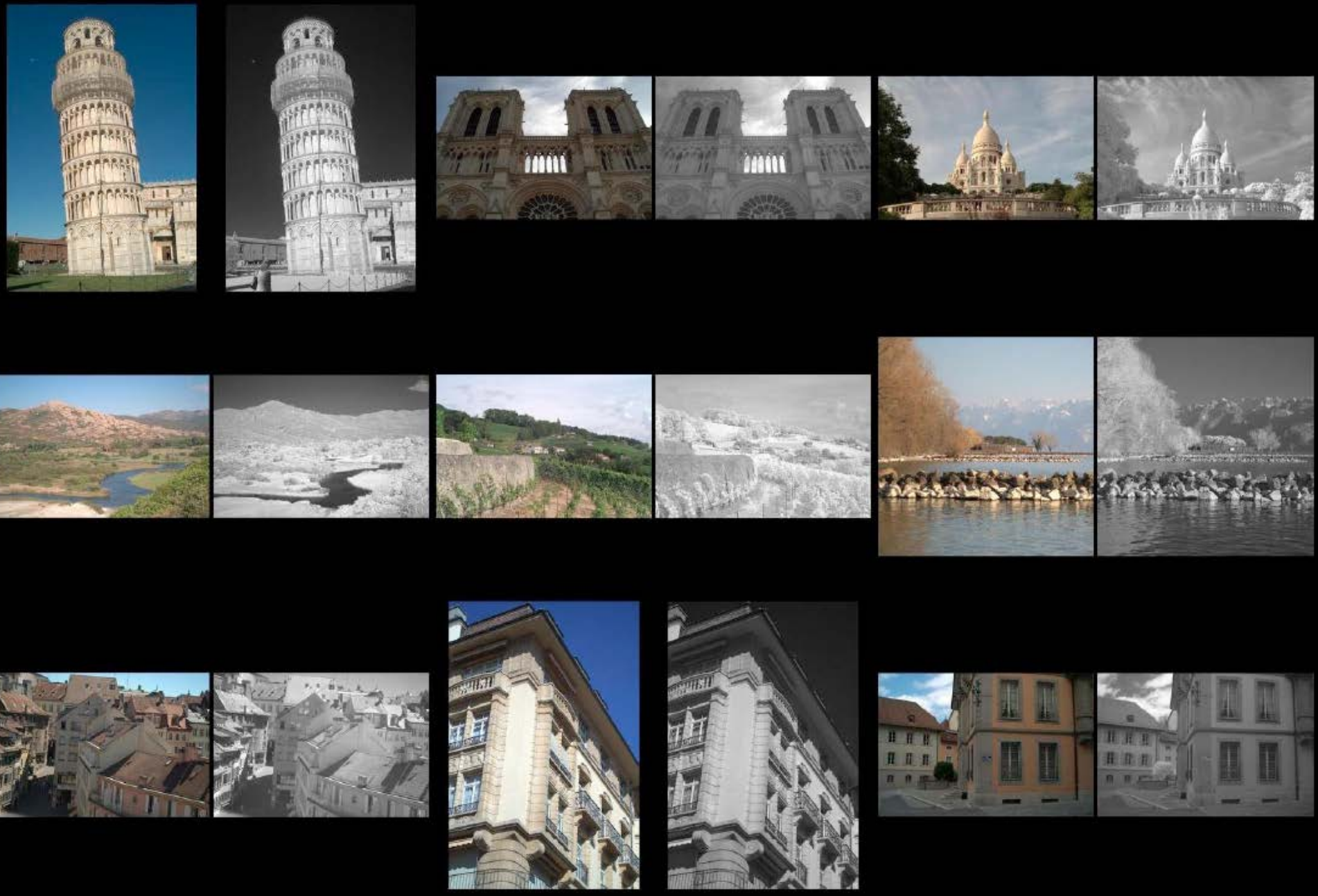
Multiple Spectra



Visible (Red, Green, and Blue: RGB)

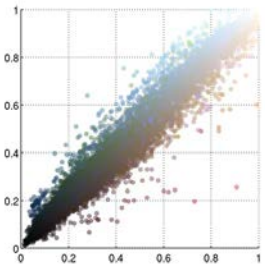
Near-infrared (NIR)

Image Database (477 RGB+NIR)

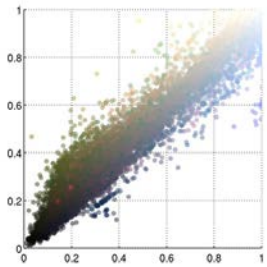


Correlation between RGB and NIR

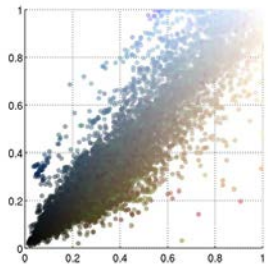
- 10’000 RGB-NIR pixel pairs, joint entropy:



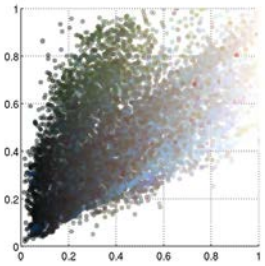
(a) R-G (4.13)



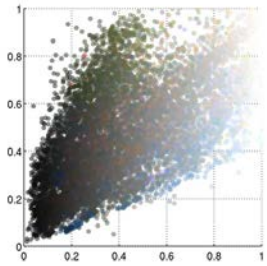
(b) B-G (4.26)



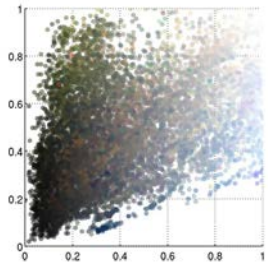
(c) R-B (4.60)



(d) R-NIR (5.29)



(e) G-NIR (5.30)

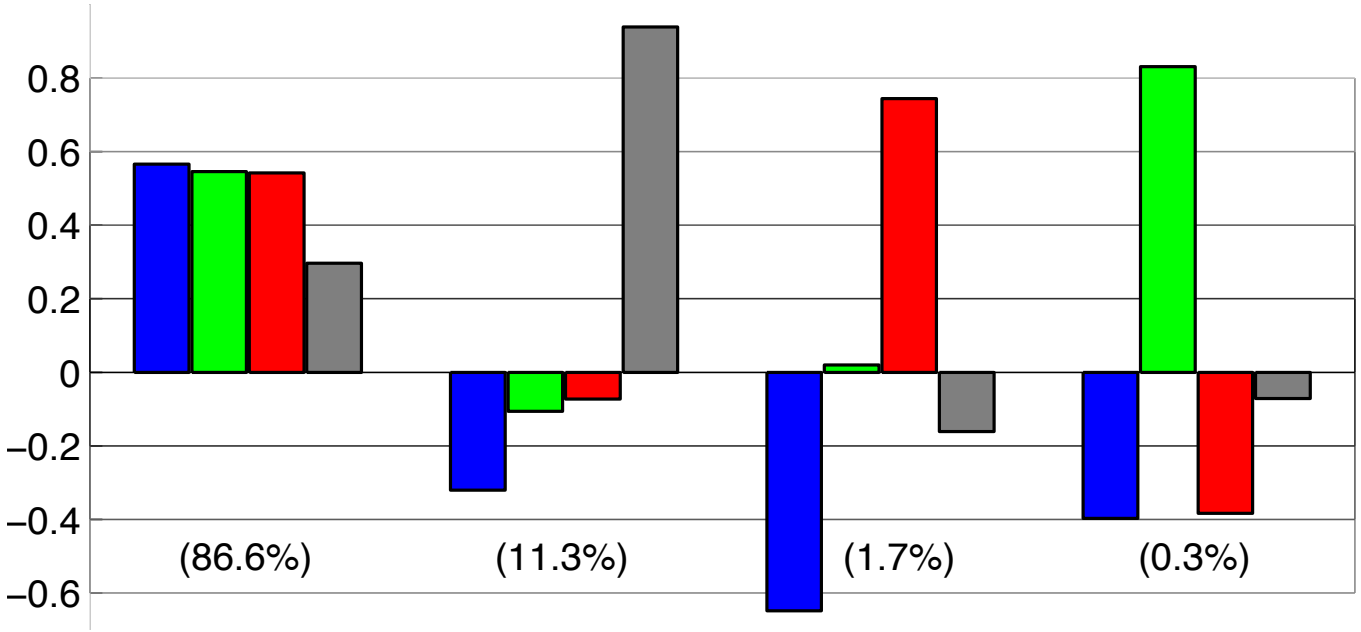


(f) B-NIR (5.44)

M. Brown and S. Süsstrunk, Multi-spectral SIFT for Scene Category Recognition, *CVPR* 2011.

Decorrelation...

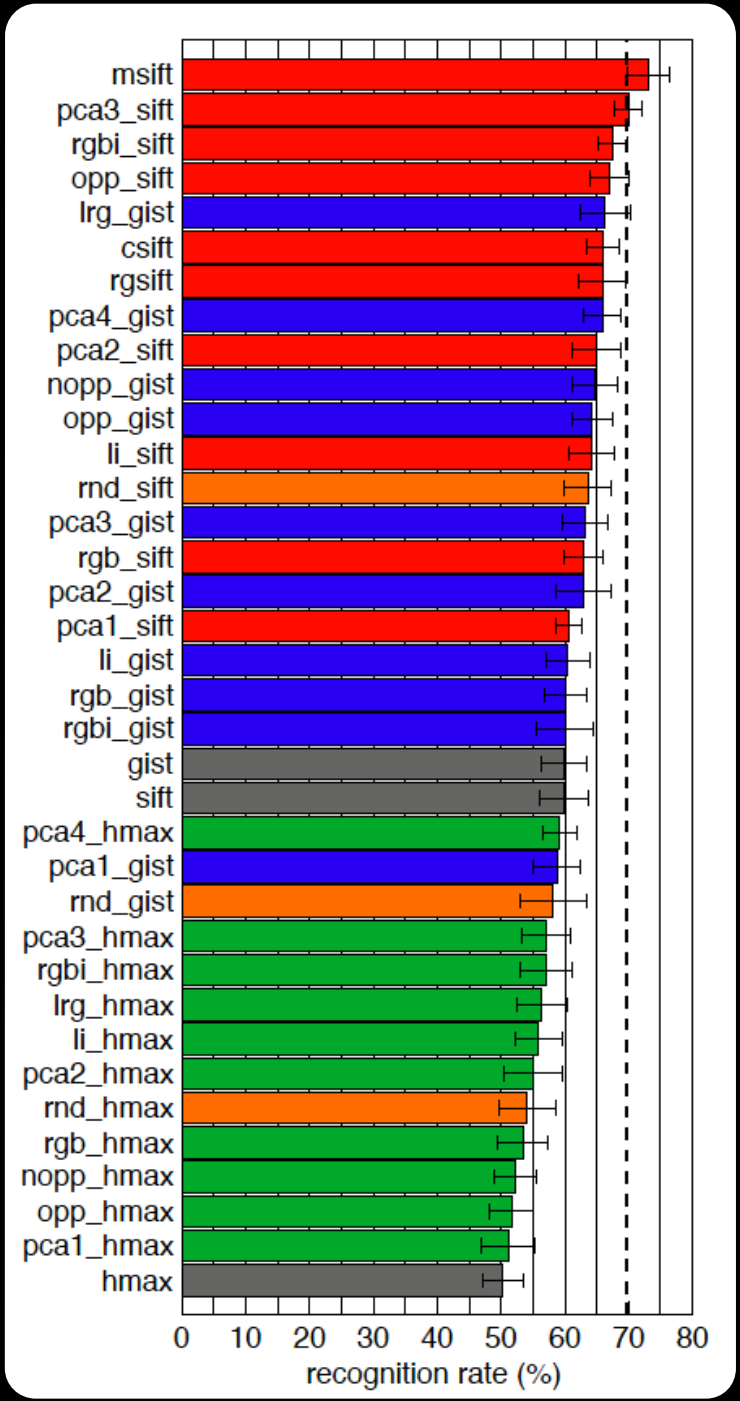
- PCA on 477 4-channel images (RGB +NIR):



M. Brown and S. Süsstrunk, Multi-spectral SIFT for Scene Category Recognition, *CVPR* 2011.

Multi-spectral SIFT

- 477 RGB+NIR images
  - 9 scene categories
- **SIFT**, **GIST**, **HMAX** descriptors.
- 11 random images per class for training, rest for testing.
  - Repeated 10 times
- ***MSIFT*** (=pca 4) statistically significantly ***outperforms*** the others.



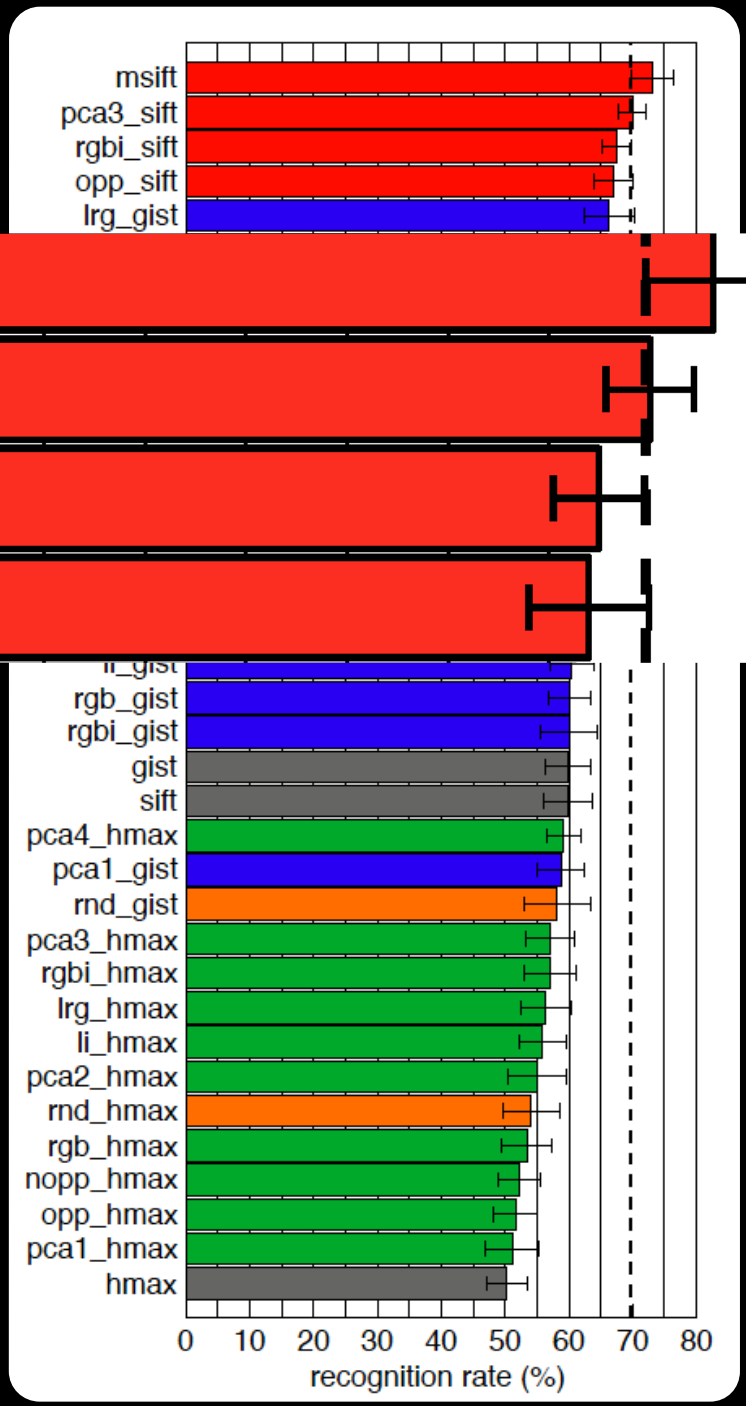
M. Brown and S. Süsstrunk, Multi-spectral SIFT for Scene Category Recognition, *CVPR* 2011.

Multi-spectral SIFT

training, rest for testing.

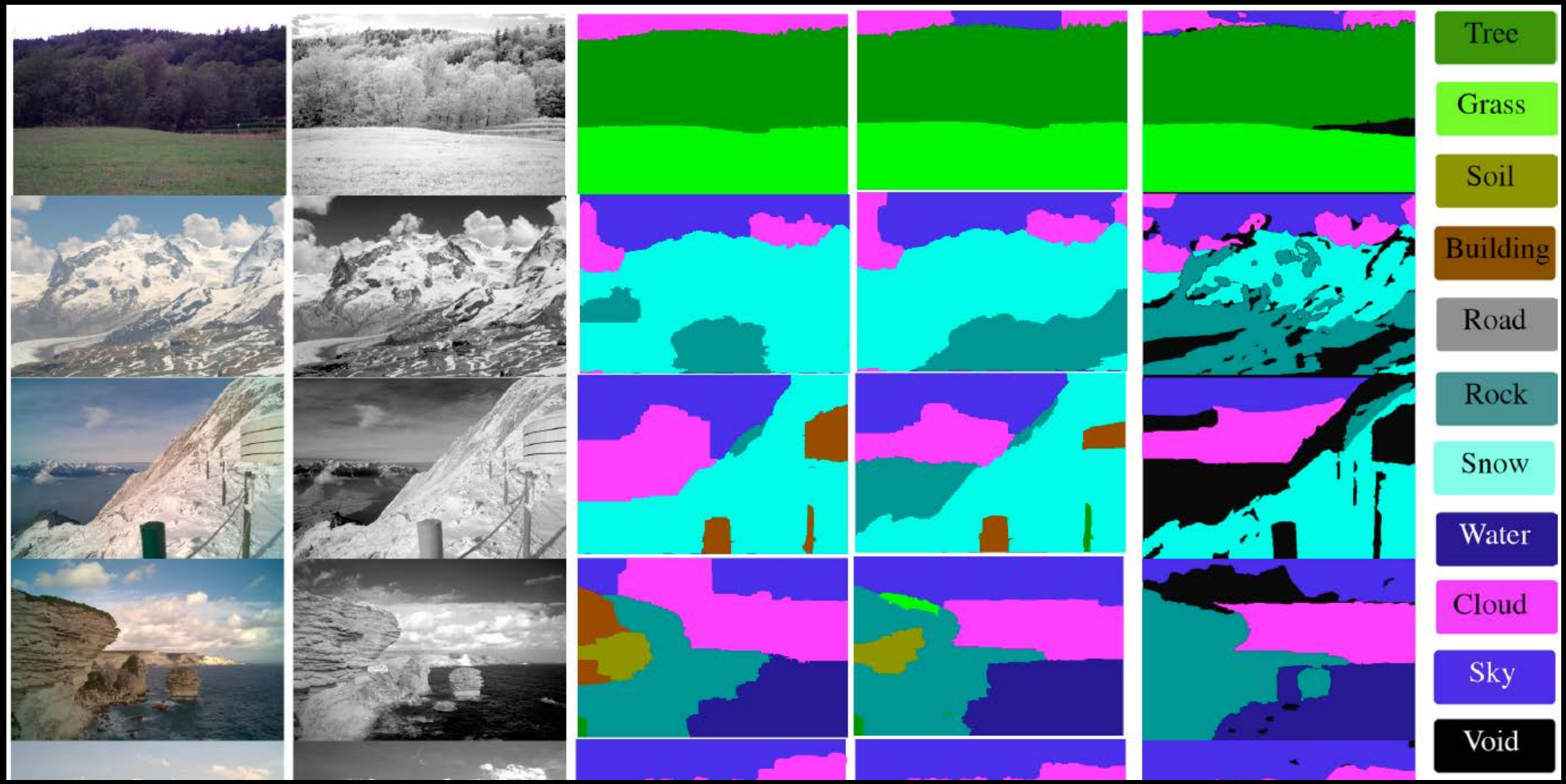
- Repeated 10 times

- ***MSIFT*** (=pca 4) statistically significantly ***outperforms*** the others.



M. Brown and S. Süsstrunk, Multi-spectral SIFT for Scene Category Recognition, *CVPR* 2011.

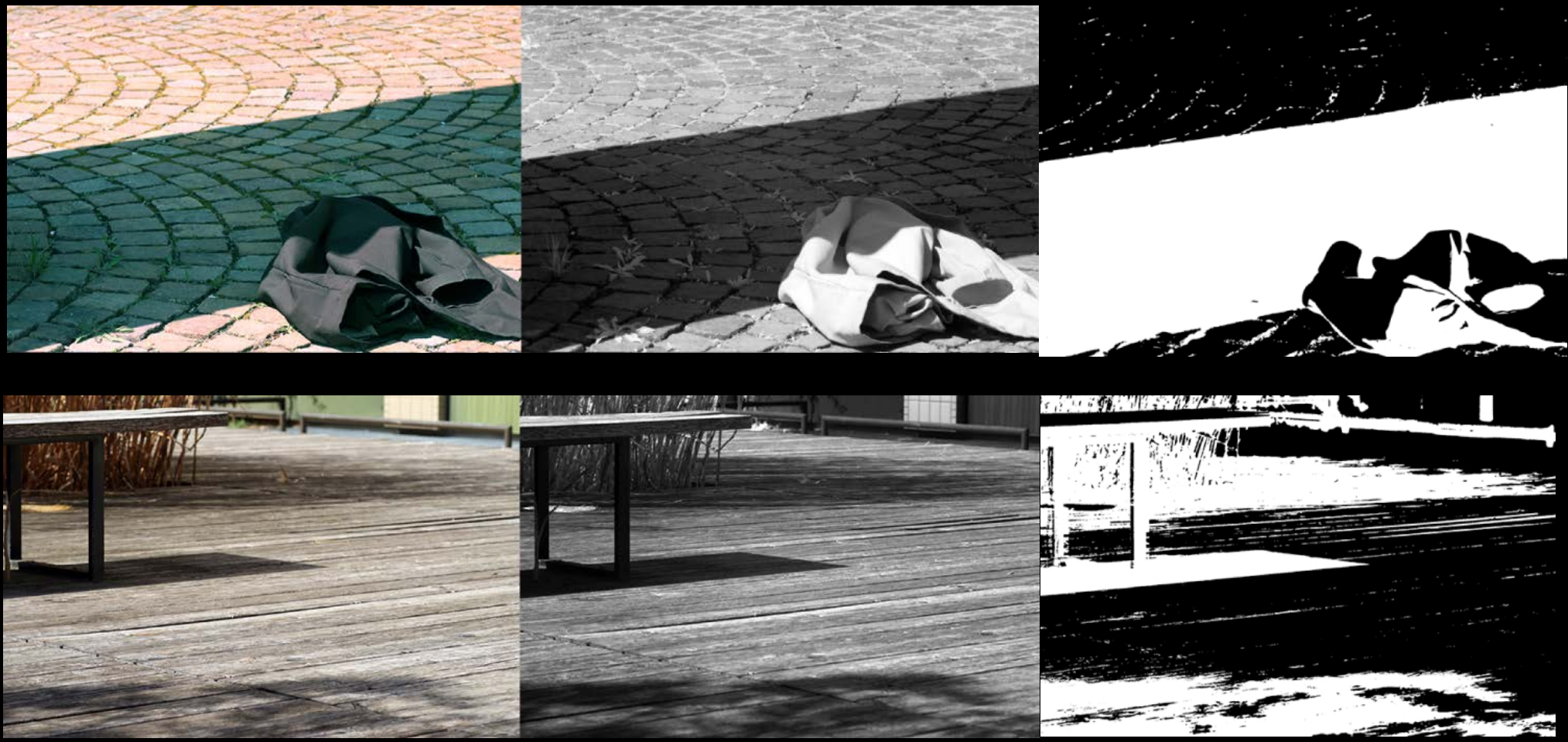
Semantic Image Segmentation



Visible NIR V Seg V+NIR Seg GT

N. Salamati, D. Larlus, G. Csurka, and S. Süsstrunk, Semantic Image Segmentation Using Visible and Near-Infrared Channels, in *ECCV's 4th Color and Photometry in Computer Vision Workshop* (2012).

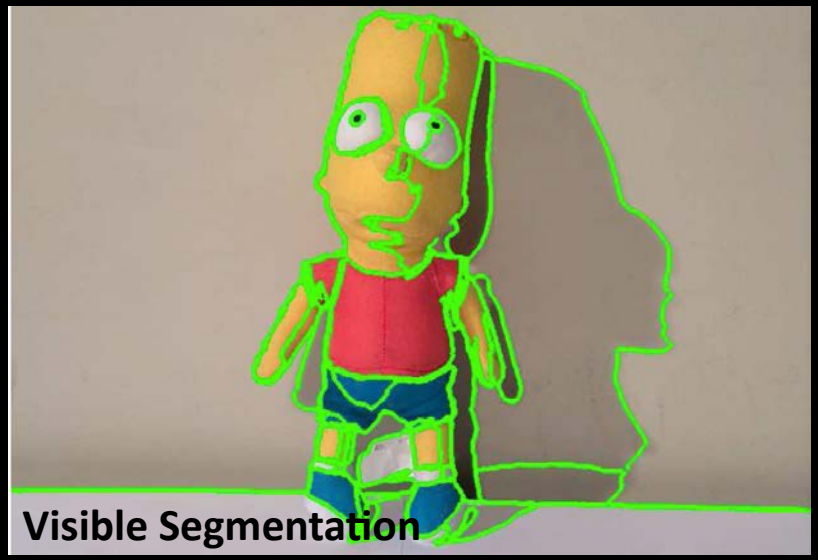
Shadow Detection



Visible NIR Binary Shadow Mask

D. Rüfenacht, C. Fredembach and S. Süsstrunk, Automatic and accurate shadow detection using near-infrared information, *IEEE Transaction on Pattern Analysis and Machine Intelligence (TPAMI)*, 2014.

Material-based Image Segmentation



N. Salamati and S. Süsstrunk, Material-Based Object Segmentation Using NIR Information, *Proc. IS&T/SID 18th Color Imaging Conference (CIC)*, 2010.

Conclusions

- In many imaging applications, the ***spectral*** dimension is often ignored.
  - the assumption is that the color channels are too correlated.
- That is suboptimal as there are many applications where ***color (contrast) is key***:
  - Saliency, super-pixels,...***and many others***!
- Beyond the visible spectrum, the "colors" are even ***less correlated***.
  - Near-infrared is a practical extension to current capture.

Acknowledgments

- ***Saliency:***
  - RK Achanta, S. Hemami, F. Estrada, A. Shaji
- ***Superpixels/Voxels:***
  - RK Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua, G. Yildirim.
- ***Near-Infrared:***
  - M. Brown, C. Fredembach, Z. Sadeghipoor, D. Rüfenacht, N. Salamati, D. Larlus, G. Csurka
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  - Swiss National Science Foundation, Hasler Foundation, Xerox Foundation.
- ***Publications:*** **ivrg.epfl.ch/publiations**