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Computer Vision
Segmentation

WS 2019/2020

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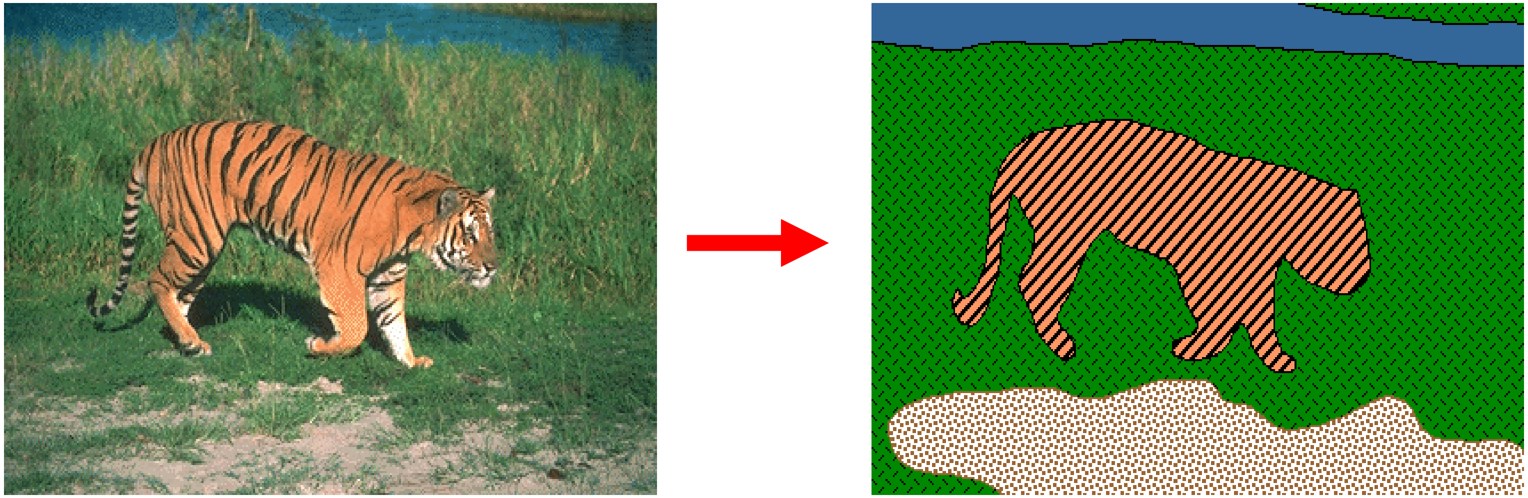
Content

- Segmentation: Motivation, definition, and applications
- Region Growing
- K-means for segmentation
- Superpixels: SLIC
- Adaptive Seeding for Superpixels and Supervoxels

What is Segmentation?

- Segmentation subdivides an image into its constituent regions (Gonzalez/Woods)
- Segmentation belongs to the oldest and hardest problems in computer vision



- Q: Why do we segment images?
- A: To obtain a simpler representation that is easier and faster to analyze

[Images: Kristen Grauman]

What is Segmentation?

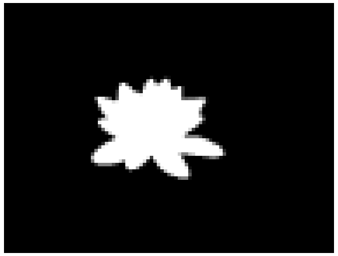
According to Klette 2014:

- Segmentation partitions an image into regions called

Segments S_i, $i = 1, \ldots, n$, such that

1. $S_i \neq \emptyset$, for any $i \in \{1, \ldots, n\}$
2. $\bigcup_{i=1}^{n} S_i = \Omega$
3. $S_i \cap S_j = \emptyset$, for all $i, j \in \{1, \ldots, n\}$ with $i \neq j$

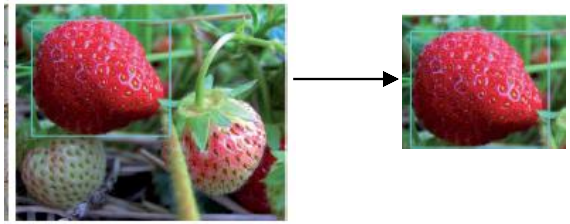
Note: Definition does not fit to all segmentation methods, because sometimes the regions can overlap. It fits especially well to superpixel methods.



Why segmentation?

Segmentation as preprocessing for many applications:

- Photo editing:



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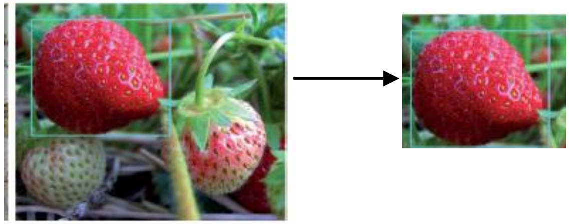
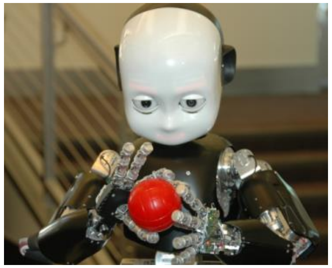


- Robotics:



Why segmentation?

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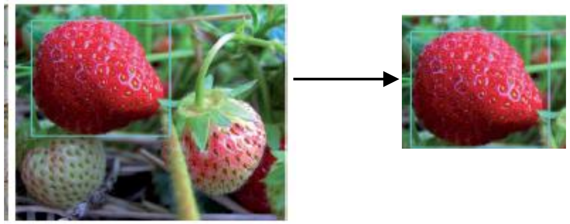
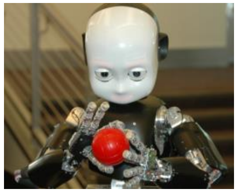
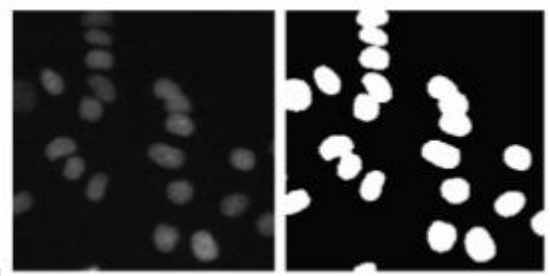
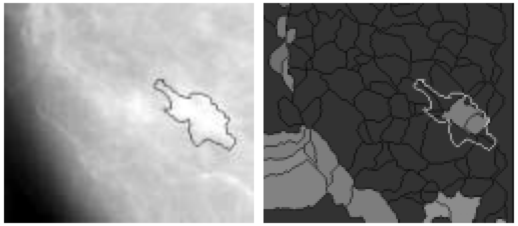


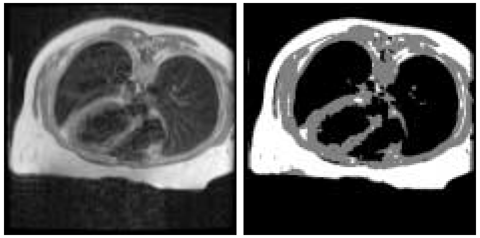
- Robotics:



- Medical image processing (e.g. X-Ray, MRI, CT, …):
  - Diagnosis (e.g. tumor detection)
  - Computer-aided surgery
  - Quantification (number of cancer cells, size of tumor)

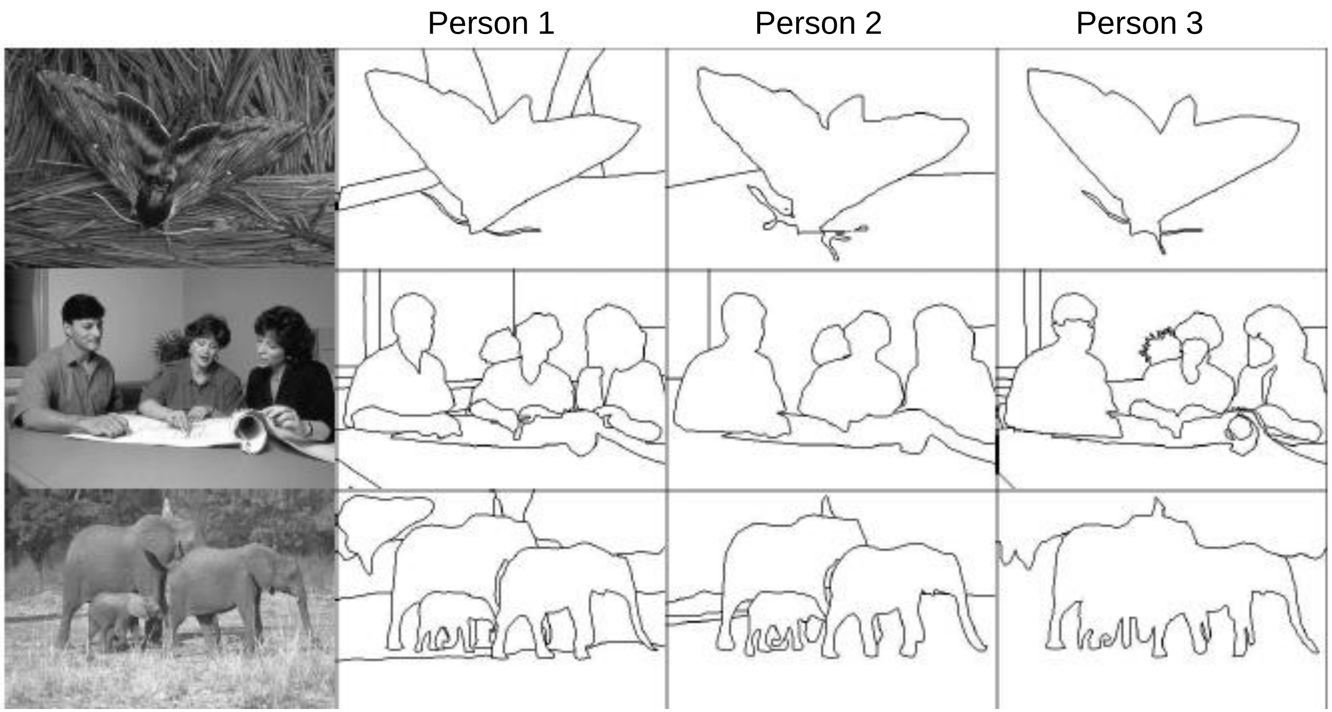






What is "good"?

- Q: How do we know if a segmentation is "good"?
- A: Compare with human performance:
- **The Berkeley Segmentation Dataset and Benchmark** (https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/)

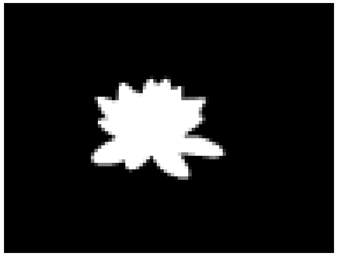


1000 images
12000 segmentations
30 subjects

[Martin et al. ICCV 2001]

Level of Detail

- The required level of detail depends on the application

- Is this what we want?
- Or should every leaf be a segment?

- Usually, some parameters can be adapted to obtain more or less segments

Over- vs Undersegmentation

- Oversegmentation:
  get more segments than desired
- Undersegmentation:
  get less segments than desired
- It is very hard (and often impossible)
  to obtain the optimum between the two


Human segmentation

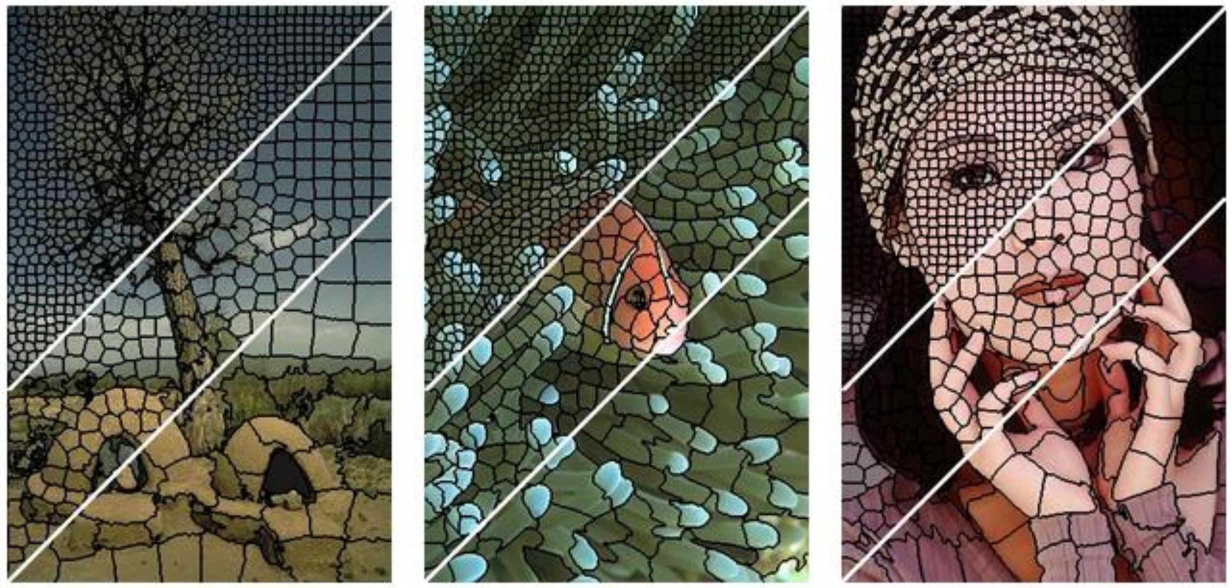

Oversegmentation


Undersegmentation

[Sigut et al. 2015]

Superpixels

- Superpixels are a different name for the segments obtained by a segmentation algorithm
- Usually, they
  - come from a strong over-segmentation (they resemble “large pixels”)
  - have a coherent, perceptually uniform appearance (color, texture)
- Example: SLIC superpixels (Achanta et al. 2010):



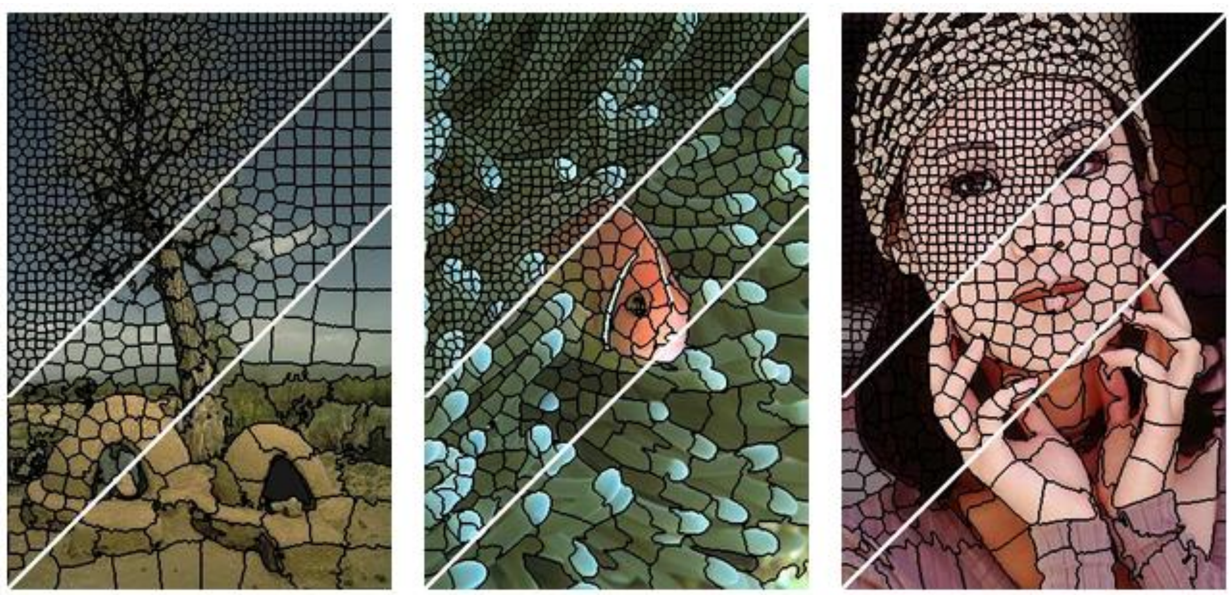
[Achanta 2010]

Superpixels

Advantage of superpixels:

Reduce computational complexity.

Much less superpixels than pixels to operate on



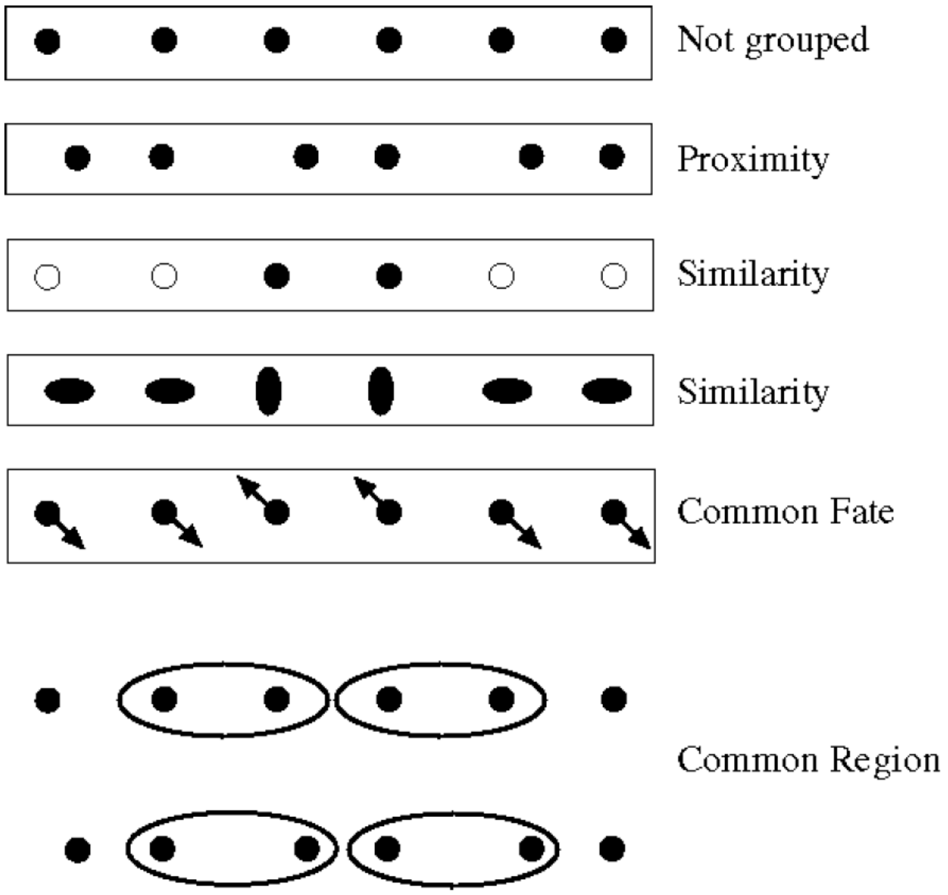
[Achanta 2010]

Segmentation in Human Vision

Human Vision:

- **Segmentation processes** exist on all levels of the visual system. They bundle parts of the visual input to perceptually coherent regions
- **Gestalt principles** group regions to larger regions

Gestalt Factors



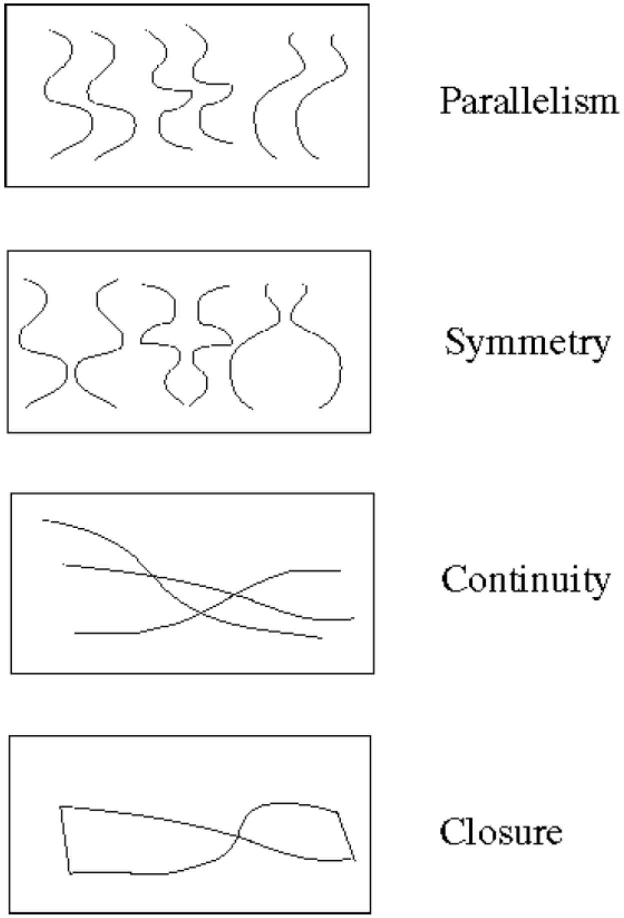
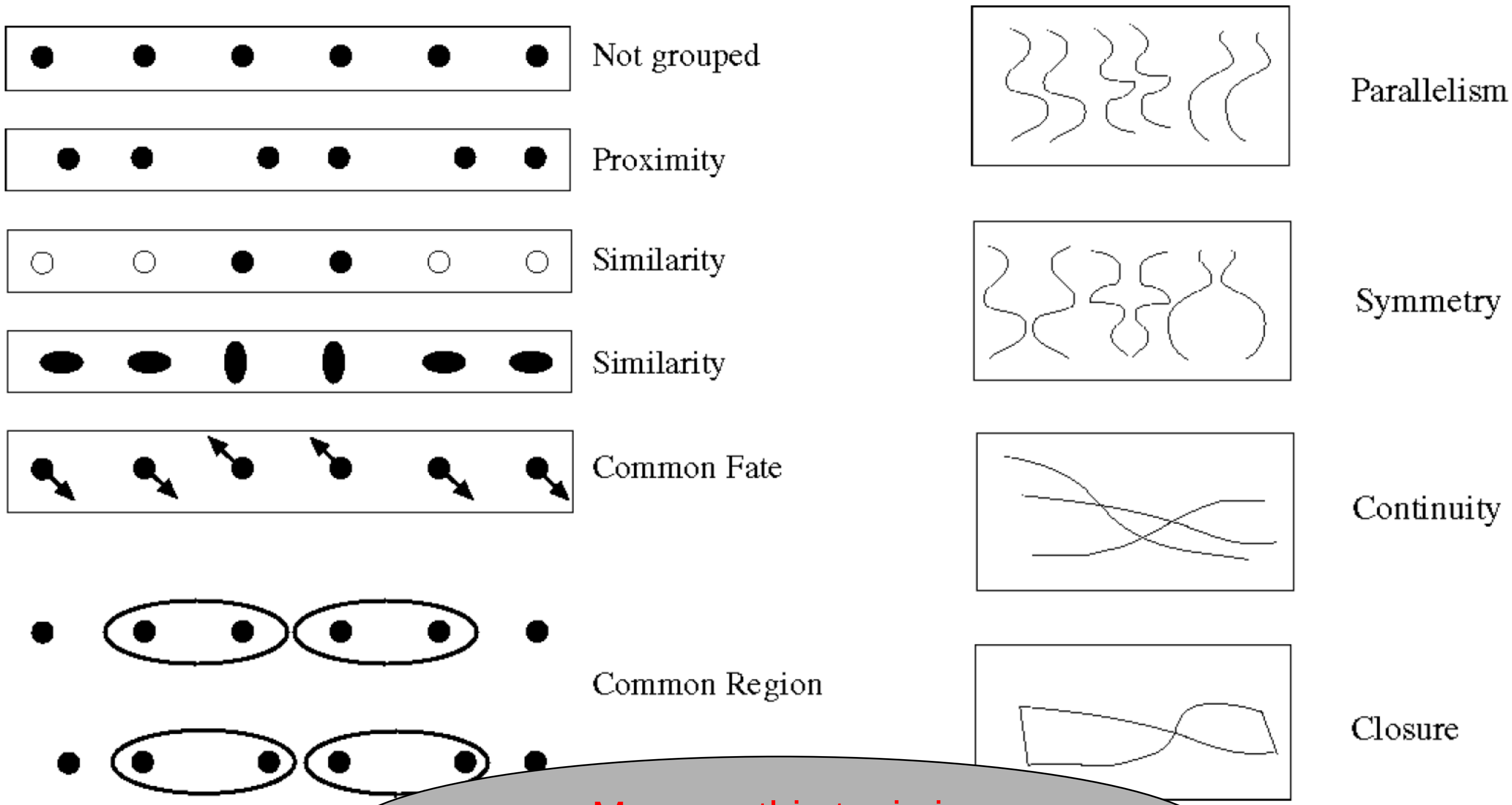


Image source: Forsyth & Ponce

Gestalt Factors



More on this topic in
“Computer Vision 2” Lecture

Image source: Forsyth & Ponce

Basics of Segmentation

- **Key elements in segmentation: proximity and similarity:**
  base segmentation on similarity of neighboring pixels
- Similarity wrt: intensity, color, texture, depth, …

- Pixels within one segment are more similar to each other than to pixels from neighboring segments
- Strong dissimilarities between neighboring segments (edges) are indicators for borders

Many segmentation approaches exist:

1 Applications
2 Thresholding
3 Clustering methods
4 Compression-based methods
5 Histogram-based methods
6 Edge detection
7 Dual clustering method
8 Region-growing methods
9 Partial differential equation-based methods
- 9.1 Parametric methods
- 9.2 Level set methods
- 9.3 Fast marching methods

10 Variational methods
11 Graph partitioning methods
- 11.1 Markov random fields
  - 11.1.1 Supervised image segmentation using MRF and MAP
  - 11.1.2 Optimization algorithms
    - 11.1.2.1 Iterated conditional modes/gradient descent
    - 11.1.2.2 Simulated annealing (SA)
    - 11.1.2.3 Alternative algorithms
  - 11.1.3 Unsupervised image segmentation using MRF and expectation maximization
  - 11.1.4 Disadvantages of MAP and EM based image segmentation
  - 11.1.5 Implementations of MRF-based image segmentation

12 Watershed transformation
13 Model based segmentation
14 Multi-scale segmentation
- 14.1 One-dimensional hierarchical signal segmentation
- 14.2 Image segmentation and primal sketch

15 Semi-automatic segmentation
16 Trainable segmentation
17 Other methods

Wikipedia: Image Segmentation

Region Growing

- Region Growing (or Seed Growing) iteratively groups pixels (seeds) into larger regions

Idea:

- Start from some seeds
- Grow regions by appending similar neighbors

1	2	1	1	0	0	0	0
1	1	9	8	7	0	0	0
1	1	9	9	0	0	0	0
2	1	8	7	1	2	1	1
1	1	1	1	1	2	1	1
1	1	1	1	1	1	1	1

Seed

For each neighbor:
Similar enough?

Region Growing

- Region Growing (or Seed Growing) iteratively groups pixels (seeds) into larger regions

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1	2	1	1	0	0	0	0
1	1	9	8	7	0	0	0
1	1	9	9	0	0	0	0
2	1	8	7	1	2	1	1
1	1	1	1	1	2	1	1
1	1	1	1	1	1	1	1

Repeat recursively

For each neighbor:
Similar enough?

Region Growing

- Region Growing (or Seed Growing) iteratively groups pixels (seeds) into larger regions

Idea:

- Start from some seeds
- Grow regions by appending similar neighbors

1	2	1	1	0	0	0	0
1	1	9	8	7	0	0	0
1	1	9	9	0	0	0	0
2	1	8	7	1	2	1	1
1	1	1	1	1	2	1	1
1	1	1	1	1	1	1	1

Final result

Region Growing

- Region Growing (or Seed Growing) iteratively groups pixels (seeds) into larger regions

Idea:

- Start from some seeds
- Grow regions by appending similar neighbors

Three questions:

- How to determine the seeds?
- How to define the similarity?
- When to stop growing?

Region Growing

Question 1:

- How to determine the seeds?

- Depends on the problem

Possibilities:

- Find maxima on intensity profile
- Select seeds evenly spaced on a grid
- Choose random seeds

Region Growing

Question 2:

- How to define the similarity?

- Depends on the problem

Possibilities:

- Intensity similarity
- Color similarity (in some color space)
- Texture similarity (e.g. gradient histograms)

Region Growing

Question 3:

- When to stop growing?

- Threshold on the similarity measure (compared with the seed)

Additionally possible to consider:

- Similarity of new pixel to average of region so far
- Size of region
- Shape of region

Region Growing

Region Growing algorithm:

- Select *k* seed points S_k
- For each seed point S_k:
  - Add all neighboring pixels N_i to S_k if the value of N_i is similar to S_k according to some similarity measure
  - Repeat until no pixels are added

whether the resulting segments should be allowed to overlap or not depends on the application

A recursive algorithm can be found in (Tönnies 2012)

Application

Extracting salient regions from saliency map for finding object candidates

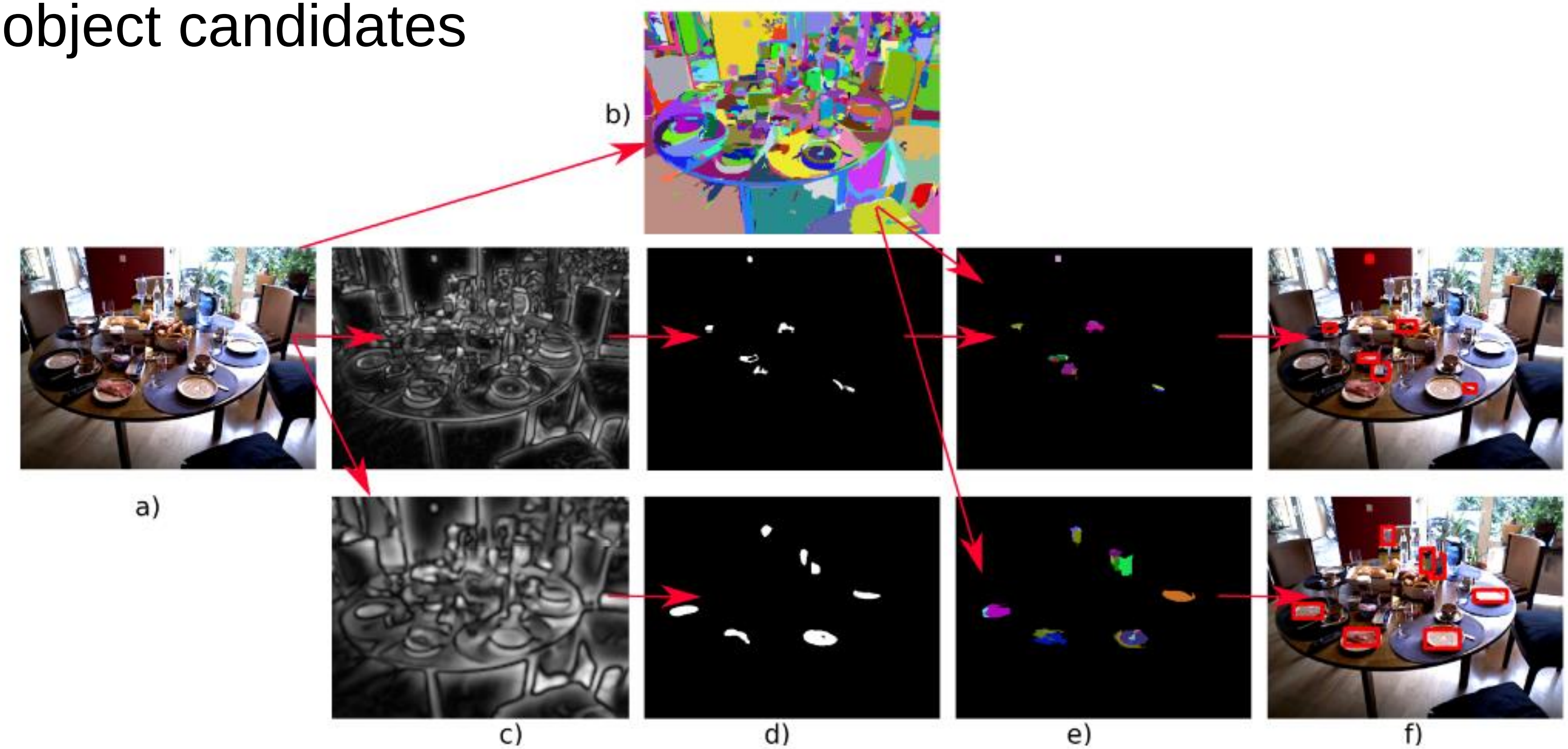


Fig. 2: Object candidate generation: a) original image, b) superpixel segmentation c) for octaves 1 and 2, their specific saliency maps, d) salient blobs obtained by region-growing, e) combining superpixels into object candidates with help of salient blobs, and e) bounding boxes of the object candidates.

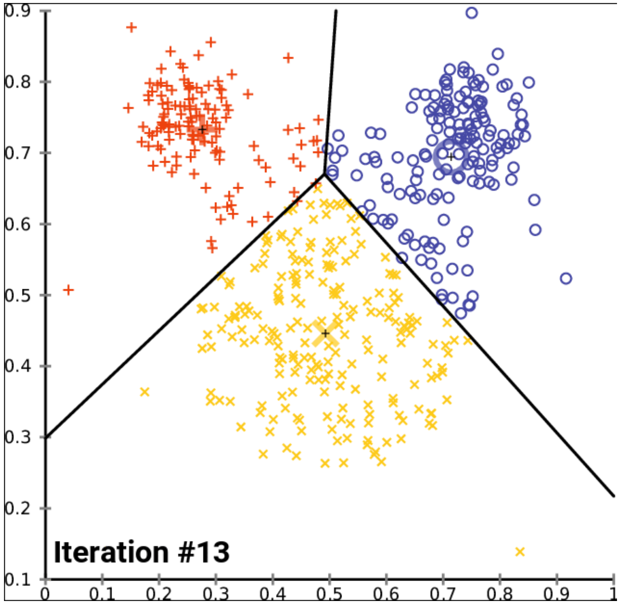
[Horbert et al, ICRA 2015]

Segmentation as Clustering

Clustering: group data points into clusters

K-means: cluster n data points into k clusters

Every cluster has a cluster center (the prototype)



Demo:

https://en.wikipedia.org/wiki/K-means_clustering#/media/File:K-means_convergence.gif

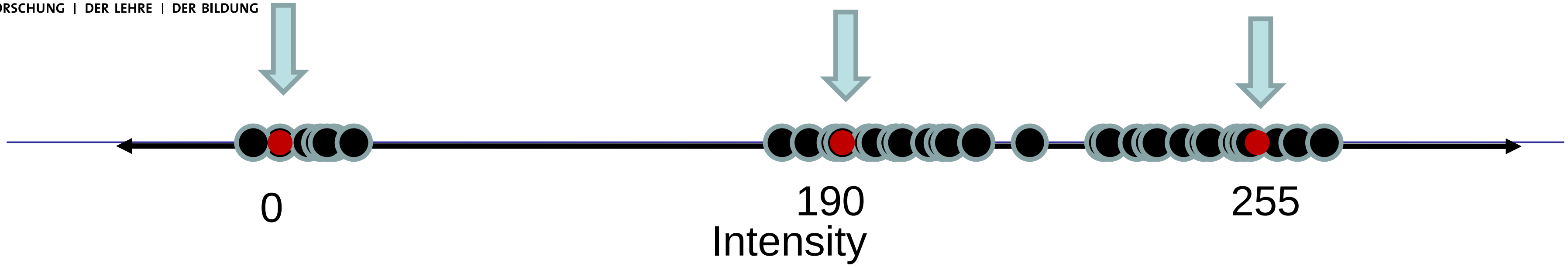
http://stanford.edu/class/ee103/visualizations/kmeans/kmeans.html

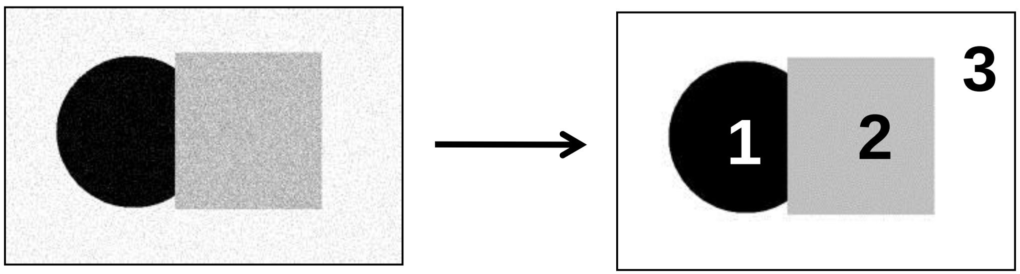
K-Means Clustering

K-Means Algorithm:

- randomly initialize the *k* cluster centers,
- iterate between two steps:
  - **Assignment:** Assign each data point to the nearest cluster (compute distance to the cluster centers and choose closest center)
  - **Update:** Recompute cluster centers
- Repeat until convergence

- Properties
  - Will always converge to *some* solution
  - Can be a “local minimum”

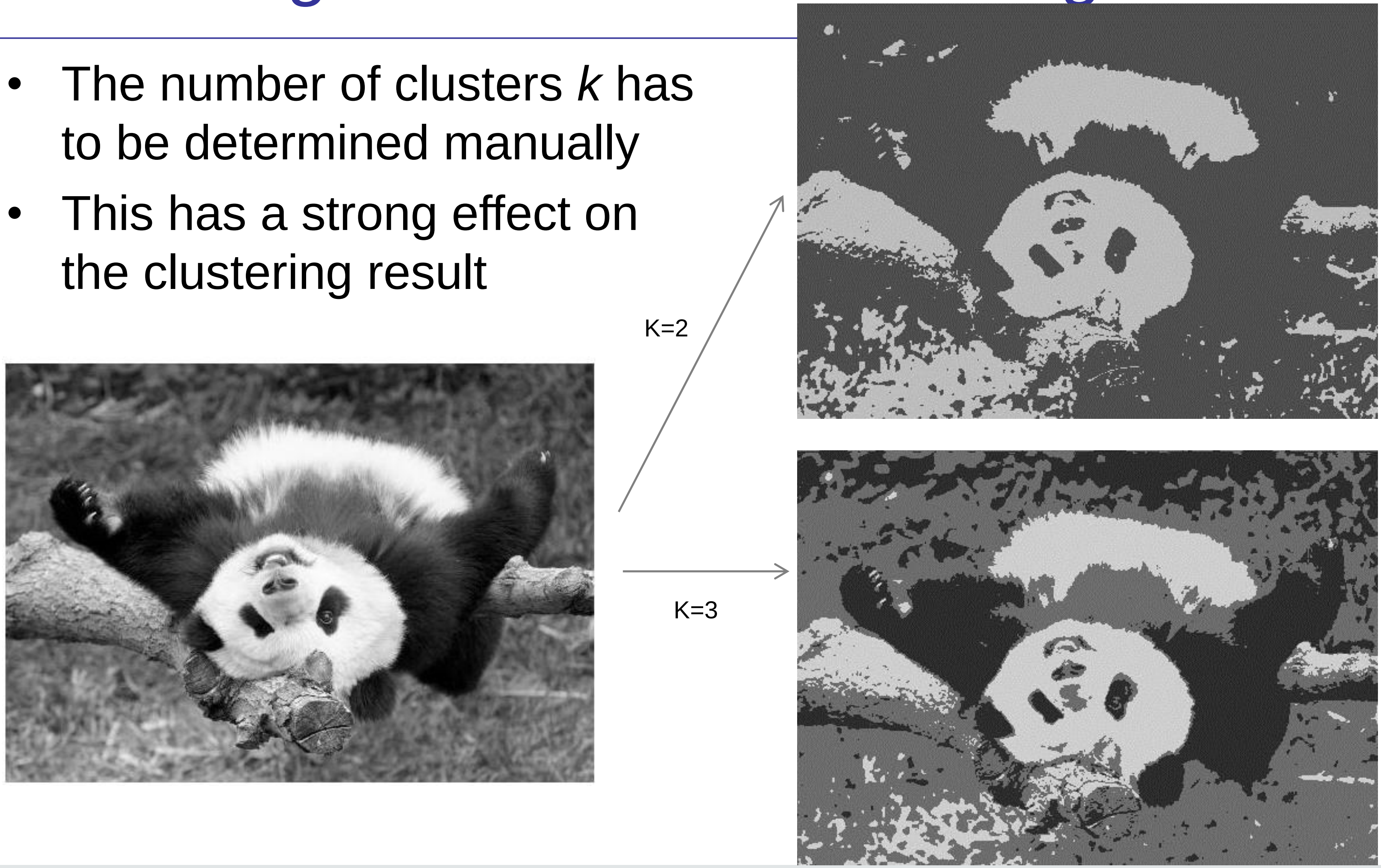




choose three “centers” as the representative intensities, and label every pixel according to which of these centers it is nearest to.

Segmentation as Clustering

- The number of clusters *k* has to be determined manually
- This has a strong effect on the clustering result



Feature Space

- Depending on what we choose as the *feature space*, we can group pixels in different ways.

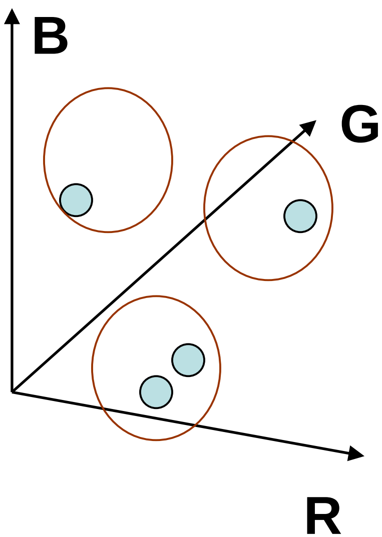
- Grouping pixels based on intensity similarity

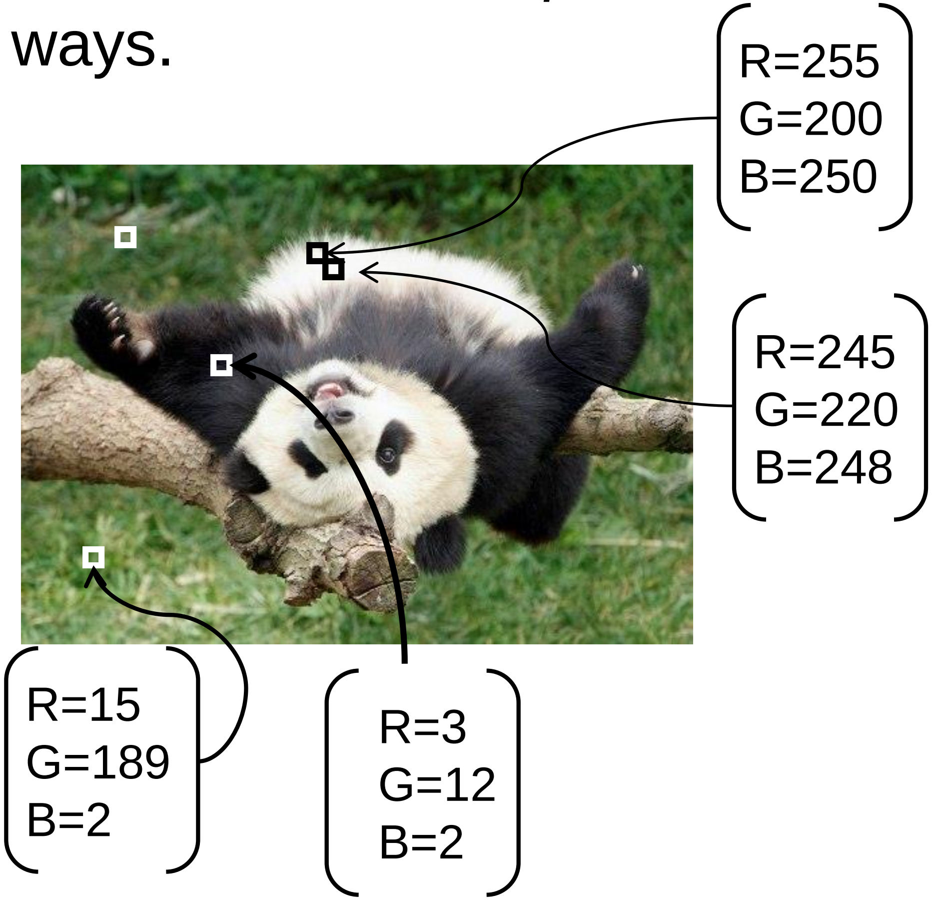
- Feature space: intensity value (1D)

Feature Space

- Depending on what we choose as the *feature space*, we can group pixels in different ways.

- Grouping pixels based on color similarity



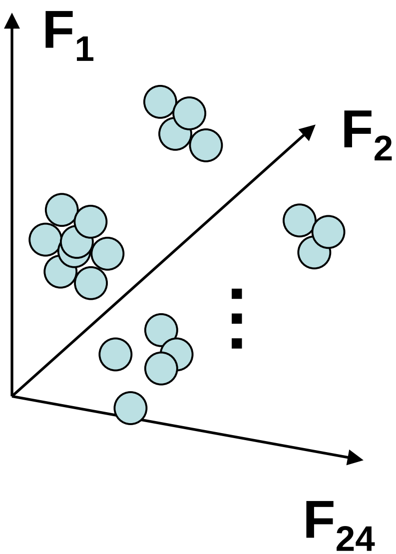


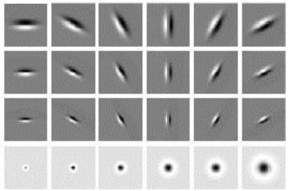
- Feature space: color value (3D)

Feature Space

- Depending on what we choose as the *feature space*, we can group pixels in different ways.

- Grouping pixels based on texture similarity



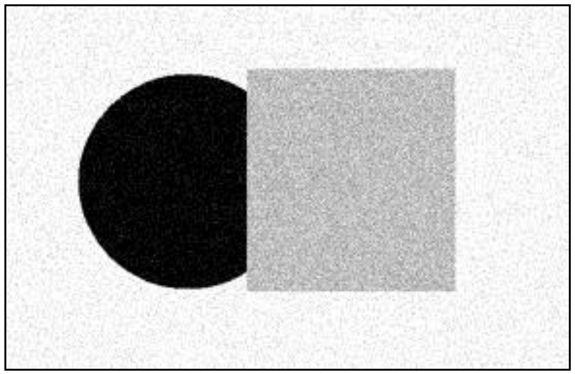


Filter bank of 24 filters

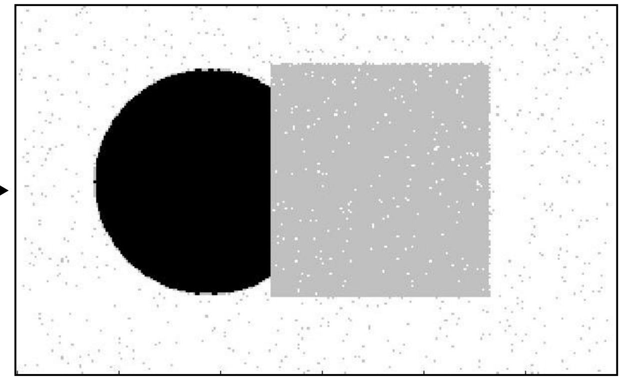
- Feature space: filter bank responses (e.g., 24D)

Spatial coherence

- Assigning a cluster label per pixel may yield outliers:



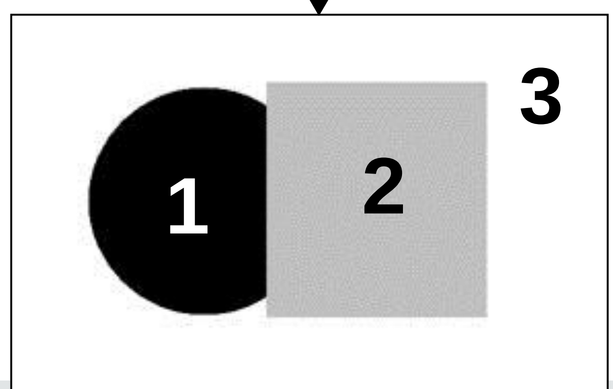
Original



Labeled by cluster center's intensity

?

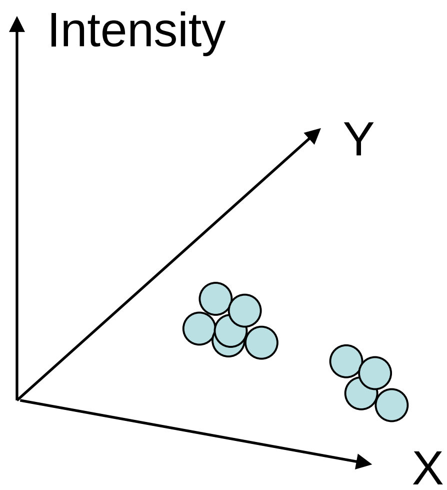
- How can we ensure they are spatially smooth?

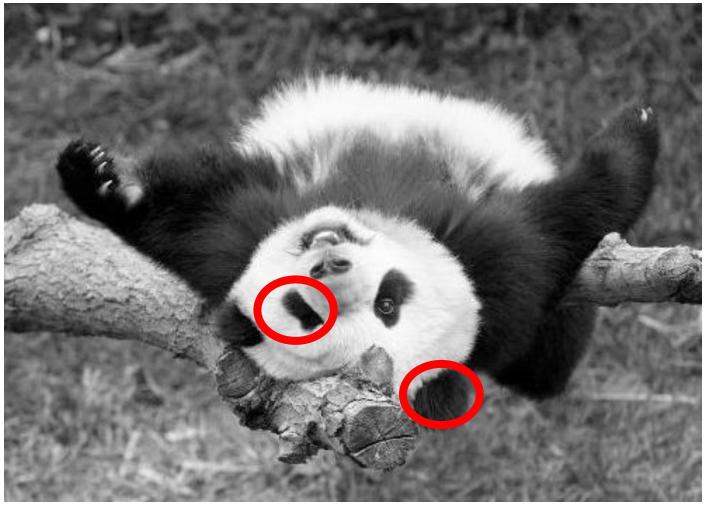


Spatial coherence

- Depending on what we choose as the *feature space*, we can group pixels in different ways.

- Grouping pixels based on *intensity+position* similarity



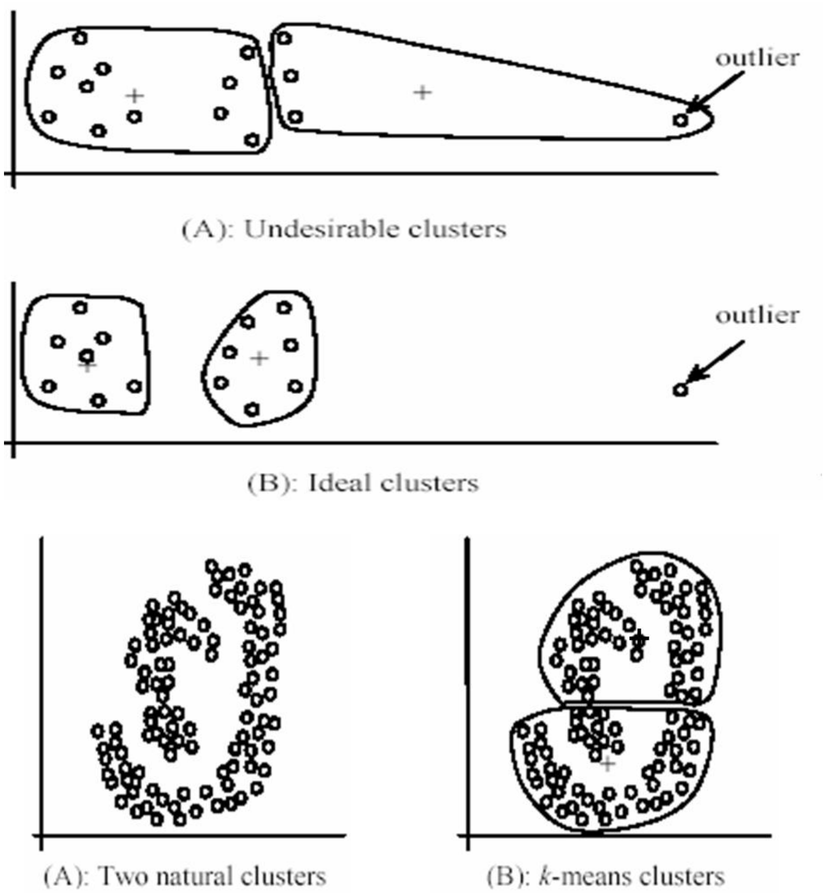


⇒ Simple way to encode both *similarity* and *proximity.*

Summary K-Means

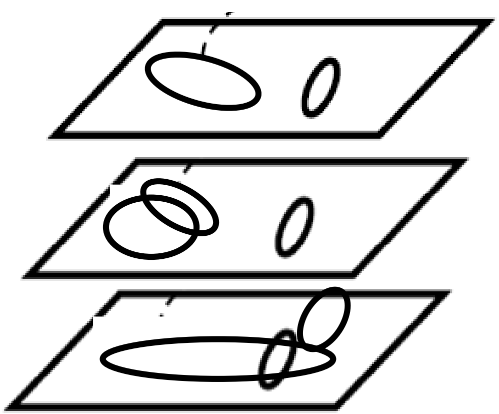
- Pros
  - Simple, fast to compute
  - Converges to local minimum of within-cluster squared error

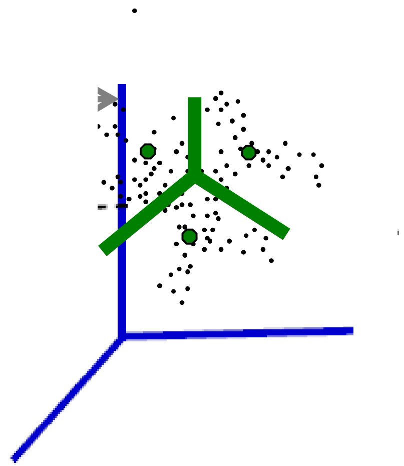
- Cons/issues
  - Setting k?
  - Sensitive to initial centers
  - Sensitive to outliers
  - Detects spherical clusters only



Application of K-means

Generate visual words: Map high-dimensional descriptors (e.g. SIFT) to tokens/words by quantizing the feature space





Descriptor space

- **Determine which word to assign to each new image region by finding the closest cluster center.**

Nister, David, and Henrik Stewenius. "Scalable recognition with a vocabulary tree." *2006 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'06)*.IEEE, 2006.

K-means – still up to date

Google Scholar

k-means

Articles

About 18.900 results (**0,12** sec)

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Clustering is a classic topic in optimization with **k-means** being one of the most fundamental such problems. In the absence of any restrictions on the input, the best-known algorithm for **k-means** in Euclidean space with a provable guarantee is a simple local search heuristic ...
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V Cohen-Addad, PN Klein, C Mathieu - SIAM Journal on Computing, 2019 - SIAM
We give the first polynomial-time approximation schemes (PTASs) for the following problems:(1) uniform facility location in edge-weighted planar graphs;(2) k-median and **k-means** in edge-weighted planar graphs; and (3) **k-means** in Euclidean space of bounded ...
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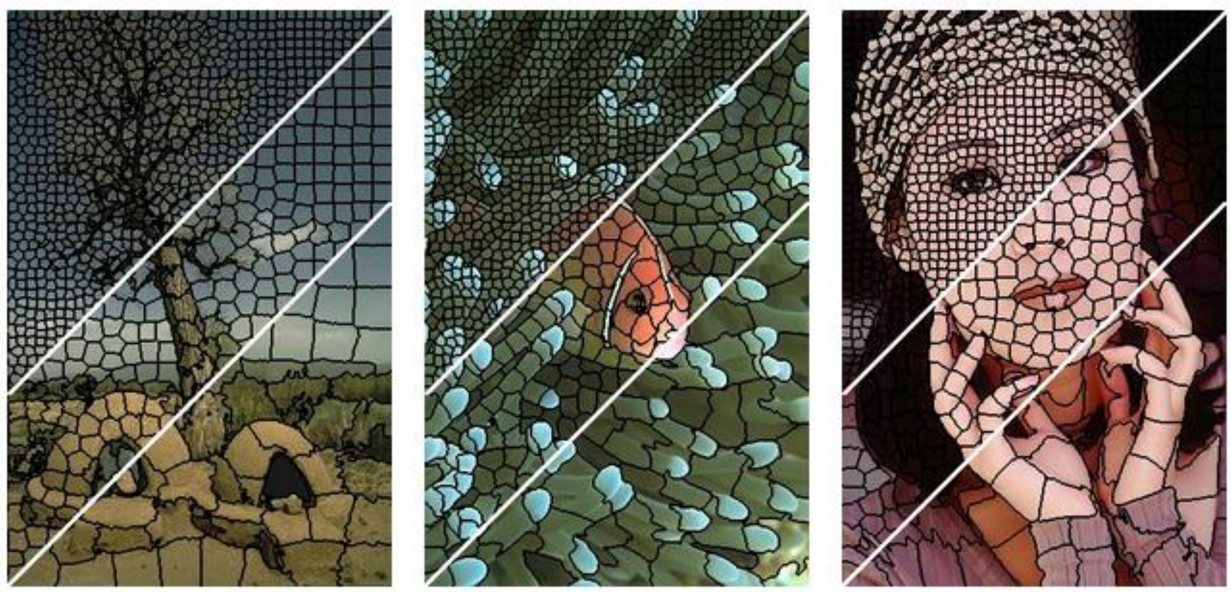
Local Search Yields a PTAS for k-Means in Doubling Metrics
Z Friggstad, M Rezapour, MR Salavatipour - SIAM Journal on Computing, 2019 - SIAM
The most well-known and ubiquitous clustering problem encountered in nearly every branch of science is undoubtedly **k-means**: given a set of data points and a parameter k, select k centers and partition the data points into k clusters around these centers so that the sum of ...
Cited by 68 Related articles All 7 versions

Superpixels

Remember

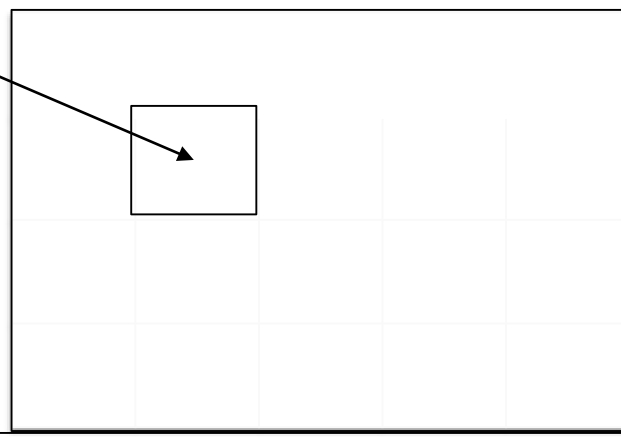
- Superpixels are a different name for the segments obtained by a segmentation algorithm
- Usually, they
  - come from a strong over-segmentation (they resemble “large pixels”)
  - have a coherent, perceptually uniform appearance (color, texture)
- Example: SLIC superpixels (Achanta et al. 2010):



[Achanta 2010]

SLIC Superpixels

- SLIC: **Simple Linear Iterative Clustering**
- SLIC superpixels are based on a local version of k-means
- SLIC is **very fast** to compute and **memory-efficient**
- Apply k-means to a local region on a regularly sampled grid:



Radhakrishna Achanta

	Citations	year
SLIC superpixels compared to state-of-the-art superpixel methods R Achanta, A Shaji, K Smith, A Lucchi, P Fua, S Süsstrunk IEEE transactions on pattern analysis and machine intelligence 34 (11), 2274 ...	2464 *	2012

SLIC Superpixels

Algorithm:

- Initiate k cluster centers, sampled regularly on grid
- Move centers to point of minimal gradient intensity
- Repeat until convergence:
  - Assign each pixel to its nearest cluster centers
  - Adjust cluster center to mean color and position

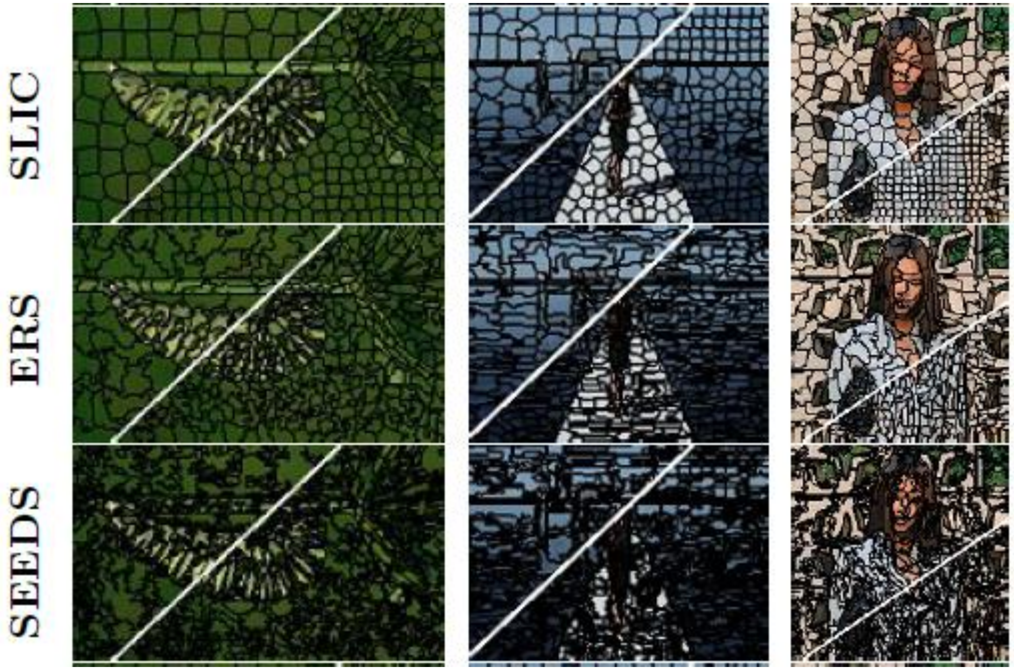
SLIC Superpixels

Number of superpixels: 500

Number of superpixels: 100

Superpixel Evaluation

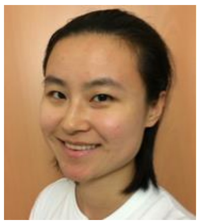
- Superpixel Evaluation Framework: http://davidstutz.de/projects/superpixel-benchmark/
- (Stutz, Hermans, Leibe: CVIU 2018)
- Evaluation of 28 superpixel algorithms on 5 datasets



„we recommend 6 algorithms for use in practice, thereby covering a wide range of application scenarios: **ETPS** [84], **SEEDS** [80], **ERS** [47], **CRS** [78, 79], **ERGC** [68] and **SLIC** [74]."

Adaptive Superpixel Seeding

Use prior map to determine superpixel resolution



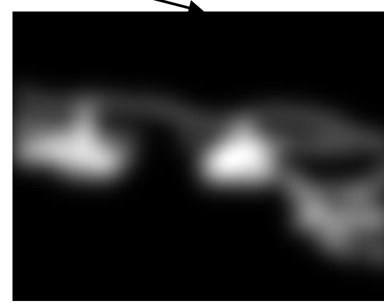
Ge Gao

Christian Wlms

Saliency prior

Edge prior

IROS 2017



GCPR 2017

- Wilms/Frintrop: Edge Adaptive Seeding for Superpixel Segmentation, Proc. of the German Conference on Pattern Recognition (GCPR), 2017
- IROS 2017: Gao, Lauri, Zhang, Frintrop: Saliency-guided Adaptive Seeding for Supervoxel Segmentation

Summary

- Segmentation methods partition the image into segments
- The literature on segmentation is huge, the task is still considered unsolved. Which algorithm to choose depends highly on the application
- We have seen two simple but effective algorithms: region growing and k-means
- More sophisticated methods will be covered in the summer term lecture “Computer Vision 2”

Primary Literature

Gonzalez/Woods, 4th ed, 2018

Region growing:

- Toennies, Klaus D. "Segmentation: Principles and Basic Techniques." *Guide to Medical Image Analysis*. Springer London, 2012. 171-209

K-means

- Bishop, Christopher M. "Pattern recognition." *Machine Learning* 128 (2006)

Secondary Literature

- Martin, David, et al. "A database of human segmented natural images and its application to evaluating segmentation algorithms and measuring ecological statistics." *Computer Vision, 2001. ICCV 2001. Proceedings. Eighth IEEE International Conference on*. Vol. 2. IEEE, 2001.
- Achanta, Radhakrishna, et al. „SLIC superpixels". No. EPFL-REPORT-149300. 2010.
- Horbert, Esther, et al. "Sequence-level object candidates based on saliency for generic object recognition on mobile systems." *Robotics and Automation (ICRA), 2015 IEEE International Conference on*. IEEE, 2015.
- Arthur, David, and Sergei Vassilvitskii. "k-means++: The advantages of careful seeding." *Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*. Society for Industrial and Applied Mathematics, 2007.
- Achanta, Radhakrishna, et al. "SLIC superpixels compared to state-of-the-art superpixel methods." *IEEE transactions on pattern analysis and machine intelligence* 34.11 (2012): 2274-2282.
- Jose Sigut, Francisco Fumero, Omar Nuñez: *Over- and Under-Segmentation Evaluation based on the Segmentation Covering Measure,* WSCG 2015 Conference on Computer Graphics, Visualization and Computer Vision
- Tönnies, Klaus D. *Grundlagen der Bildverarbeitung*. Vol. 11. München: Pearson Studium, 2005.