Answers to questions in
Lab 3: Image segmentation

Name: ____Clément Gousseau________ Program: ___MSc in Computer Science____________

Instructions: Complete the lab according to the instructions in the notes and respond to the questions stated below. Keep the answers short and focus on what is essential. Illustrate with figures only when explicitly requested.

Good luck!

Question 1: How did you initialize the clustering process and why do you believe this was a good method of doing it?

Answers:
I initialized the centers of the clusters by randomly picking a pixel from the image. I believed it was a good choice of doing it since this random pick would hopefully be representative of the color distribution.

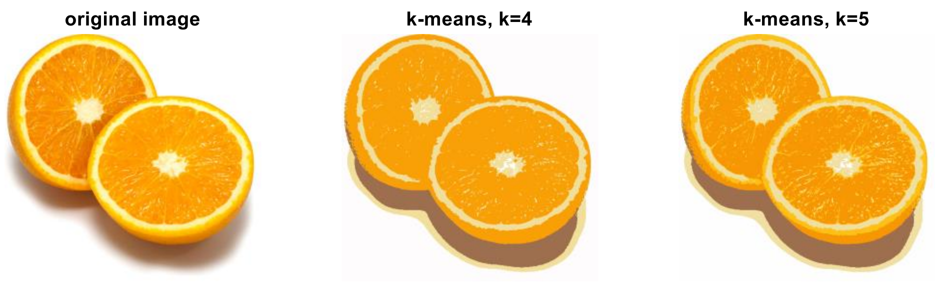
Question 2: How many iterations L do you typically need to reach convergence, that is the point where no additional iterations will affect the end results?

Answers:
For the orange image:

K=3; 16 iterations (mean over 10 simulations)
K=5; 27 iterations (mean over 10 simulations)
K=10; 42 iterations (mean over 10 simulations)
K=20; 78 iterations (mean over 10 simulations)

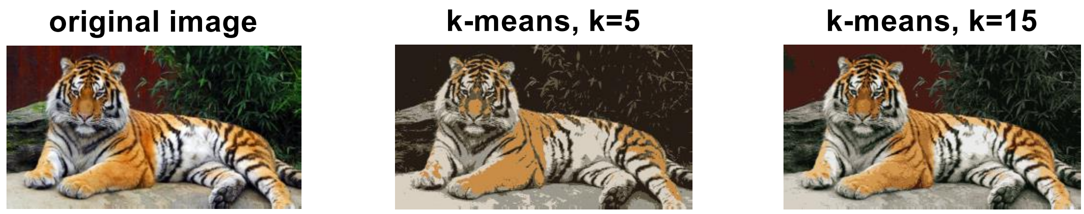
Question 3: What is the minimum value for K that you can use and still get no superpixel that covers parts from both halves of the orange? Illustrate with a figure.

Answers:



Question 4: What needs to be changed in the parameters to get suitable superpixels for the tiger images as well?

Answers:
Since the image is more complex K must be increased. And since K increases, more iterations are needed for the algorithm to converge.



Question 5: How do the results change depending on the bandwidths? What settings did you prefer for the different images? Illustrate with an example image with the parameter that you think are suitable for that image.

Answers:
When the spatial bandwidth is small and the color bandwidth is large, only pixels which are close to each others are clustered together.
When the color bandwidth is small and the spatial bandwidth is large, more importance is given to the colors; pixels with similar color are clustered together. There is some spatial incoherence.
When both bandwidths are small, a lot of importance is given to both space and colors so there are many clusters. On the contrary when both bandwidths are small there are few clusters.

Small spatial bandwidth (5), large color bandwidth (100)

Small color bandwidth (5), large spatial bandwidth (50)

Small color bandwidth (3), small spatial bandwidth (3)

Small color bandwidth (20), small spatial bandwidth (20)

Good setting: spatial bandwidth=4; color bandwidth=5

Question 6: What kind of similarities and differences do you see between K-means and mean-shift segmentation?

Answers:

Similarities:

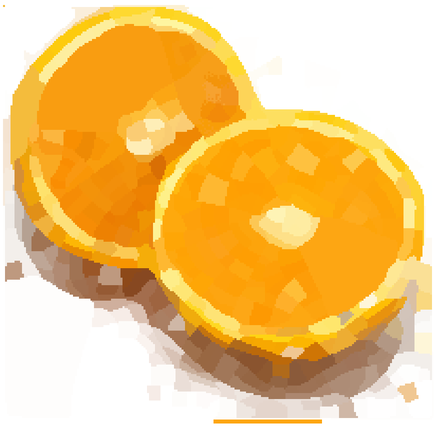
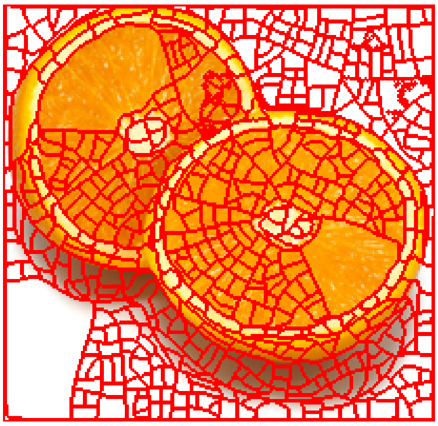
- Both use an iterative process to perform image segmentation
- With reasonable settings they both present color coherence (pixels with similar colors are grouped together)

Differences:

- There is spatial coherence with mean-shift (pixels with similar color are not grouped together if they are separated by another color). There is no spatial coherence with k-means (pixels with similar color are not grouped together even if they are separated by another color).
- With K-means the number of cluster K is an input whereas the number of clusters is not fixed with mean-shift

Question 7: Does the ideal parameter setting vary depending on the images? If you look at the images, can you see a reason why the ideal settings might differ? Illustrate with an example image with the parameters you prefer for that image.

Answers:

ncuts_thresh = 0.5, min_area = 50, max_depth = 20


ncuts_thresh = 0.8, min_area = 10, max_depth = 20

Good setting depends on the level of complexity in the image.
For the orange image the main features of the image are large so we can use a high min_area. There are not many color variations so the ncuts_thresh can be low.
For the tiger image there are a lot of small details so the min_area must be small. There are many color variations so the ncuts_thresh must be high.

Question 8: Which parameter(s) was most effective for reducing the subdivision and still result in a satisfactory segmentation?

Answers:
The three parameters ncuts_thresh, min_area and max_depth have an influence on the number of subdivisions but it seems max_depth is most effective for reducing the subdivision since it directly affects the number of possible cuts.

Question 9: Why does Normalized Cut prefer cuts of approximately equal size? Does this happen in practice?

Answers:

From the formula $Ncut(A,B) = cut(A,B) \times (\frac{1}{assoc(A,V)} + \frac{1}{assoc(B,V)})$

With $assoc(V) = assoc(A,V) + assoc(B,V) - cut(A,B)$

So $\frac{\partial Ncut(A,B)}{\partial assoc(A,V)} = cut(A,B) \times \left(\frac{-1}{assoc(A,V)^2} + \frac{1}{\left(assoc(V)+cut(A,B)-assoc(A,V)\right)^2}\right)$

So $\frac{\partial Ncut(A,B)}{\partial assoc(A,V)} = \alpha(assoc(A,V)^2 - \left(assoc(V) + cut(A,B) - assoc(A,V)\right)^2)$

Which is equal to 0 if $assoc(A,V) = \frac{(assoc(V)+cut(A,B))^2}{2\times(assoc(V)+cut(A,B))}$.

By symmetry we have the same result: $\frac{\partial Ncut(A,B)}{\partial assoc(B,V)} = 0$ if $assoc(B,V) = \frac{(assoc(V)+cut(A,B))^2}{2\times(assoc(V)+cut(A,B))}$

So Ncut(A,B) is minimized if the two cuts have the same size.

Question 10: Did you manage to increase *radius* and how did it affect the results?

Answers:

It was possible to increase the radius but this makes the computation much longer so it was not possible to try large values. It enables to create more complex shapes since the graph is more complex

Radius=10

Radius=3

Question 11: Does the ideal choice of *alpha* and *sigma* vary a lot between different images? Illustrate with an example image with the parameters you prefer.

Answers:

Alpha = 8, sigma = 8

Alpha = 20, sigma = 8

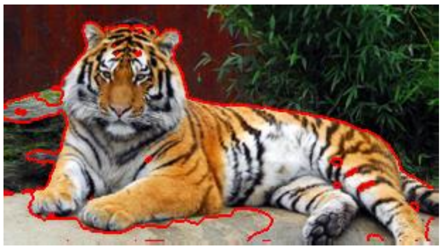
Alpha = 20, sigma = 8

Each image has a best value for sigma and alpha but we cannot really say the quality of the segmentation depends a lot on alpha and sigma.

Question 12: How much can you lower K until the results get considerably worse?

Answers:

With K=4 the results are still pretty good.

With K<3 and the results start becoming worse although there are still acceptable


Question 13: Unlike the earlier method Graph Cut segmentation relies on some input from a user for defining a rectangle. Is the benefit you get of this worth the effort? Motivate!

Answers:
In our case the rectangle contains the relevant information so it is useful for the classification. However this is not a very generalizable technique since in more complex systems we can't afford a human help to guide the algorithm for every image.

Question 14: What are the key differences and similarities between the segmentation methods (K-means, Mean-shift, Normalized Cut and energy-based segmentation with Graph Cuts) in this lab? Think carefully!!

Answers:

Similarity:
- These algorithms segment the image based on spatial/color similarities between pixels
- They are iterative processes
- They have parameters that affect the number of segments and more generally the quality of segmentation. The best setting depends on the image.

Differences:
- Mean-shift algorithm uses the position information in addition to color
- Normalized cuts and graph cuts consider the image as a graph
- Graph cuts uses a Bayesian approach