

Problem Statement

(40 points) Image Segmentation using mean shift.

Input image: 3/data/baboonColor.png.

Take this 512 512 pixel image, smooth it using Gaussian convolution with standard deviation 1 pixel width, and subsample the smoothed image by a factor of 2 in each spatial dimension to produce a 256 256 image. Use this smaller-sized image for the following experiment. If this image is still too large for your computers memory, then you may resize further.

Implement the algorithm for mean-shift image segmentation using both color (RGB) and spatial coordinate (XY) features. Tune parameters suitably to get a segmented image with at least 5 segments and no more than 50 segments. To improve code efficiency, you may use Matlab functions like `knnsearch()`, `bsxfun()`, etc. For this image, about 20 iterations should be sufficient for reaching close to convergence. You may select a random subset of nearest neighbors, in feature space, for the mean-shift updates to reduce running time. Each iteration can run in about 10-20 seconds on a typical personal computer.

1. Write a function `myMeanShiftSegmentation.m` to implement this.
2. Display the (i) original image along with (ii) the segmented image that shows color-coded pixels (and, thus, segments) using the color component of the converged feature vectors.
3. Report the following parameter values: Gaussian kernel bandwidth for the color feature, Gaussian kernel bandwidth for the spatial feature, number of iterations.

Code

Mean Shift Segmentation

```
1 function [outputImage] = myMeanShiftSegmentation(inputImage ,  
    numIterations , spaceSigma , intensitySigma)  
2     k = 400;  
3  
4     indices = double(zeros(size(inputImage , 1)^2, 2));  
5  
6     count = 0;  
7     for j = 1:size(inputImage , 1)  
8         for i = 1:size(inputImage , 1)  
9             count = count + 1;  
10            indices(count , :) = double([i , j]);  
11        end  
12    end  
13
```

```

14     imageRepresentation = double([indices, reshape(
        inputImage, [size(inputImage, 1)^2, 3])]);
15     newImageRepresentation = double(zeros(size(
        imageRepresentation)));
16
17     for iter = 1:numIterations
18         iter
19         f = bsxfun(@(x,y) x./y, imageRepresentation,
        sqrt(2)*[spaceSigma, spaceSigma,
        intensitySigma, intensitySigma,
        intensitySigma]);
20         [IDX, D] = knnsearch(f, f, 'K', k);
21
22         for count = 1:size(inputImage, 1)^2
23             nbrs = imageRepresentation(IDX(
                count, 2:end), :);
24             wts = exp(-(D(count, 2:end))
                .^2));
25             u = sum(bsxfun(@(x,y) x.*y, nbrs
                , wts'));
26             sum_wts = sum(wts);
27             u = u/sum_wts;
28             newImageRepresentation(count, :)
                = double([
                imageRepresentation(count, 1)
                , imageRepresentation(count,
                2), u(1, 3:end)]);
29         end
30         sum(sum(abs(imageRepresentation -
                newImageRepresentation)))/(size(
                imageRepresentation,1))
31         imageRepresentation = newImageRepresentation;
32
33     end
34     outputImage = uint8(round(reshape(imageRepresentation(:,
        3:5), [size(inputImage, 1), size(inputImage, 1), 3])
        ));
35 end

```

Implementation Details

We considered the algorithm with a 128x128 image due to lack of computing power leading to increased computation time. We took $K = 400$ nearest neighbors and took their weighted average to determine the mean shift. Note that the weights were determined by a 5 dimensional Gaussian vector in space (X, Y) and color (R, G, B). We updated just the color values keeping the position coordinates intact. This was repeated over $N = 20$ iterations for the algorithm to converge.

Result Images



Optimum Parameters

hs = 16

hr = 25

Number of Iterations = 20