

# MSML640: Computer Vision

## Assignment 3

### Instructions

1. Answer sheets, code and input/output images must be submitted on Canvas. Hard copies will not be accepted.
2. Please provide a pdf version of your answer sheet named: LastName\_FirstName\_ASN3.pdf.
3. Please use '.py' as file extension.
4. Please put all your code, input/output images and answer sheets in a folder (no subdirectories). Make sure your code is bug-free and works out of the box. Please be sure to submit all main and helper functions. Be sure to not include absolute paths. Points will be deducted if your code does not run out of the box.
5. If plots are required, you must include them in your answer sheet (pdf) and your code must display them when run. Points will be deducted for not following this protocol.
6. Your code and plots should use the same filenames mentioned in the question (if present). Variables in your code should use the same names that are mentioned in the question (if present).
7. Please make sure that the folder is named LastName\_FirstName\_ASN3\_py.
8. Zip the above folder and name the zipped file LastName\_FirstName\_ASN3\_py.zip. Submit *only* the zip file.

### 1 Short answer problems [20 points]

1. Suppose we form a texture description using textons built from a filter bank of multiple anisotropic derivative of Gaussian filters at two scales and six orientations (as displayed below in Figure 1). Is the resulting representation sensitive to orientation, or is it invariant to orientation? Explain why.

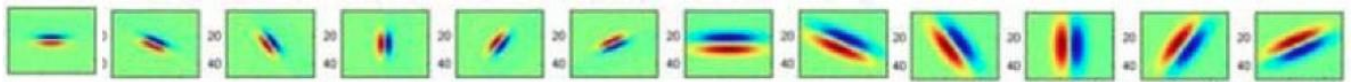


Figure 1: Filter bank

- Consider Figure 2 below. Each small square denotes an edge point extracted from an image. Say we are going to use k-means to cluster these points' positions into  $k=2$  groups. That is, we will run k-means where the feature inputs are the  $(x,y)$  coordinates of all the small square points. What is a likely clustering assignment that would result? Briefly explain your answer.

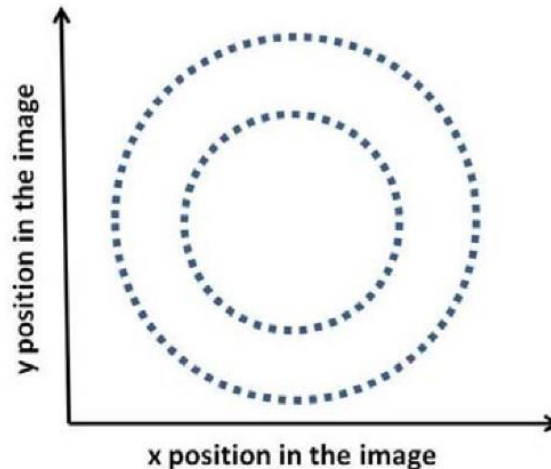


Figure 2: Edge points

- When using the Hough Transform, we often discretize the parameter space to collect votes in an accumulator array. Alternatively, suppose we maintain a continuous vote space. Which grouping algorithm (among k-means, mean-shift, or graph-cuts) would be appropriate to recover the model parameter hypotheses from the continuous vote space? Briefly describe and explain.
- Suppose we have run the connected components algorithm on a binary image, and now have access to the multiple foreground 'blobs' within it. Write pseudocode showing how to group the blobs according to the similarity of their outer boundary shape, into some specified number of groups. Define clearly any variables you introduce.

## 2 Programming [80 points]

- Color quantization with k-means. [40 points]

For this problem you will write code to quantize a color space by applying k-means clustering to the pixels in a given input image, and experiment with two different color spaces—RGB and HSV. Write Python functions as defined below. Save each function in a file called `<function-name>.py` and submit all of them.

- 5 points. Given an RGB image, quantize the 3-dimensional RGB space, and map each pixel in the input image to its nearest k-means center. That is, replace the RGB value at each pixel with its nearest cluster's average RGB value. Use the following form:

```
[outputImg, meanColors] = quantizeRGB(origImg, k)
```

where `origImg` and `outputImg` are  $M \times N \times 3$  matrices of type `uint8`, `k` specifies the number of colors to quantize to, and `meanColors` is a  $k \times 3$  array of the `k` centers. (You can use built-in k-means function in Python)

- (b) 5 points. Given an RGB image, convert to HSV, and quantize the 1-dimensional Hue space. Map each pixel in the input image to its nearest quantized Hue value, while keeping its Saturation and Value channels the same as the input. Convert the quantized output back to RGB color space. Use the following form:
- ```
[outputImg, meanHues] = quantizeHSV(origImg, k)
```
- where `origImg` and `outputImg` are  $M \times N \times 3$  matrices of type `uint8`, `k` specifies the number of clusters, and `meanHues` is a  $k \times 1$  vector of the hue centers. (You can use built-in k-means function in Python)
- (c) 5 points. Write a function to compute the SSD error (sum of squared error) between the original RGB pixel values and the quantized values, with the following form:
- ```
function [error] = computeQuantizationError(origImg, quantizedImg)
```
- where `origImg` and `quantizedImg` are both RGB images, and `error` is a scalar giving the total SSD error across the image.
- (d) 5 points. Given an image, compute and display two histograms of its hue values. Let the first histogram use equally-spaced bins (uniformly dividing up the hue values), and let the second histogram use bins defined by the `k` cluster center memberships (i.e., all pixels belonging to hue cluster `i` go to the `i`-th bin, for  $i=1, \dots, k$ ). Use the following form:
- ```
function [histEqual, histClustered] = getHueHists(im, k)
```
- where `im` is an  $M \times N \times 3$  matrix representing an RGB image, and `histEqual` and `histClustered` are the two output histograms.
- (e) 5 points. Write a script `colorQuantizeMain.py` that calls all the above functions appropriately using the provided image `fish.jpg`, and displays the results. Calculate the SSD error for the image quantized in both RGB and HSV space. Write down the SSD errors in your answer sheet. Illustrate the quantization with a lower and higher value of `k`. Be sure to convert an HSV image back to RGB before displaying with `imshow`. Label all plots clearly with titles.
- (f) 15 points. In your writeup, explain all the results. How do the two forms of histogram differ? How and why do results vary depending on the color space? The value of `k`? Across different runs?
2. Circle detection with the Hough Transform [40 points]
- Implement a Hough Transform circle detector that takes an input image and a fixed radius, and returns the centers of any detected circles of about that size. Include a function with the following form:
- ```
[centers] = detectCircles(im, radius, useGradient)
```
- where `im` is the input image, `radius` specifies the size of circle we are looking for, and `useGradient` is a flag that allows the user to optionally exploit the gradient direction measured at the edge points. The output centers is an  $N \times 2$  matrix in which each row lists the  $(x, y)$  position of a detected circles' center. Save this function in a file called `detectCircles.py` and submit it.
- Then experiment with the basic framework, and in your writeup analyze the following:
- (a) 10 points. Explain your implementation in concise steps (English, not code).
- (b) 10 points. Demonstrate the function applied to the provided images `jupiter.jpg` and `egg.jpg`. Display the accumulator arrays obtained by setting `useGradient` to 0 and 1. In each case, display the images with detected circle(s), labeling the figure with the radius. For Python, you can directly read the image pixel information in the plot.
- (c) 10 points. For one of the images, display and briefly comment on the Hough space accumulator array.
- (d) 5 points. Experiment with ways to determine how many circles are present by post-processing the accumulator array.
- (e) 5 points. For one of the images, demonstrate the impact of the vote space quantization (bin size).