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CS 558, Computer Vision
Hw2
5/4/19
Code:
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# 5/1/19
# Computer Vision hw2
# I pledge my honor that i have abided by the stevens honor system
# kms -> week 6 pg 10
# slic -> week 6 pg 41
import math
import random
import sys
import numpy as np
import cv2
# given a pixel's bgr values, and the array of centroids,
# will output the index of the shortest distance
def bgr_distance(pix, bgrlist):
  # distance funct: sqrt((r-r1)^2+(g-g1)^2+(b-b1)^2)
  b, g, r = pix
  smallest = 200000
```

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for I in range(len(bgrlist)):
    b1, g1, r1 = bgrlist[l]
    # temp skips the sqrt b/c we are just comparing
    temp = (r-r1)**2+(g-g1)**2+(b-b1)**2
    if (temp < smallest):
      smallest = temp
      index = I
  return index
# k means segmentation takes image, randomly selects points as
# initial colors, processes image and colors until convergence
def kmeans(img, k=10):
  mean_lst = []
  cluster_lst = [[] for _ in range(k)]
  rows = img.shape[0]
  columns = img.shape[1]
  # getting first k unique random samples
  while(len(mean_lst) < k):
    x = random.randint(0, columns-1)
    y = random.randint(0, rows-1)
    mean = [img.item(y, x, 0), img.item(y, x, 1), img.item(y, x, 2)]
    if (mean in mean_lst):
      continue
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mean_lst.append(mean)
# iterating through pixels until convergence
while (1):
  temp_lst = []
  # iterating through pixels
  for i in range(columns):
    for j in range(rows):
      p = [img.item(j, i, 0), img.item(j, i, 1), img.item(j, i, 2)]
      ind = bgr_distance(p, mean_lst)
      cluster_lst[ind].append(p)
  # get mean for all clusters
  for c in range(len(cluster_lst)):
    temp = [(sum(I)//len(I)) for I in zip(*cluster_lst[c])]
    temp_lst.append(temp)
  # breaking condition
  if np.all(temp_lst == mean_lst):
    break
  else:
    mean_lst = temp_lst
    for cl in cluster_lst:
      cl.clear()
  print(mean_lst)
# setting each pixel to its respective avg cluster color
for n in range(columns):
  for m in range(rows):
    curbgr = [img.item(m, n, 0), img.item(m, n, 1), img.item(m, n, 2)]
    i = bgr_distance(curbgr, mean_lst)
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img.itemset((m, n, 0), mean_lst[i][0])
      img.itemset((m, n, 1), mean_lst[i][1])
      img.itemset((m, n, 2), mean_lst[i][2])
  return img
# given an image, square filter matrix and the length,
# outputs the filtered image
def filter(img, fm, len, channel):
  height, width = img.shape
  # create black image
  res = np.zeros((height, width), dtype=img.dtype)
  off = len//2
  for j in range(off, height-off):
    for i in range(off, width-off):
      fval = block_sum(img, fm, len, j, i)
      res.itemset((j, i), fval)
  return res
# using the filtermatrix's weight distribution, adds all the values
def block_sum(img, fm, len, y, x):
  total = 0.0
  off = len//2
  # iterating through each matrix element
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for i in range(len):
      curx = x + i - off
      cury = y + j - off
      total += img.item(cury, curx) * fm[j][i]
  return total
def eudist(pix, clist):
  y, x, b, g, r = pix
  smallest = -100
  index = 0
  for I in range(len(clist)):
    y1, x1, b1, g1, r1 = clist[l]
    # temp skips the sqrt b/c we are just comparing
    temp = ((x-x1)/2)**2 + ((y-y1)/2)**2 + (r-r1)**2 + (g-g1)**2 + (b-b1)**2
    if (temp < smallest) | (smallest < 0):</pre>
      smallest = temp
      index = I
  return index
def kmeans_5d(img, cent, S):
  cluster_lst = [[] for _ in range(len(cent))]
  rows = img.shape[0]
  columns = img.shape[1]
  iter = 0
```

for j in range(len):

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while (1):
  iter += 1
  print(cent)
  new_cent = []
  # iterating through pixels
  for i in range(columns):
    for j in range(rows):
       p = [j, i, img.item(j, i, 0), img.item(
         j, i, 1), img.item(j, i, 2)]
       # get list of centers within 2Sx2S neighborhood
       eligible = []
       for w in cent:
         if (w[0] \text{ in range}(p[0]-(2*S), p[0]+(2*S)+1)) & (w[1] \text{ in range}(p[1]-(2*S), p[1]+(2*S)+1)):
            eligible.append(w)
       if (eligible == []):
         print("hey")
         continue
       ind = eudist(p, eligible)
       cluster_lst[cent.index(eligible[ind])].append(p)
  # get mean for all clusters
  for cc in range(len(cluster_lst)):
    tempt = [(sum(I)//len(I)) for I in zip(*cluster_lst[cc])]
    # ty, tx, __,_ = tempt
    # tempt = [ty, tx, img.item(ty, tx, 0), img.item(ty, tx, 1), img.item(ty, tx, 2)]
    new_cent.append(tempt)
  # breaking condition, residual error
  E = 0
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for k in range(len(cent)):
      E += abs(cent[k][0]- new_cent[k][0])
      E += abs(cent[k][1]- new_cent[k][1])
      E += abs(cent[k][2]- new_cent[k][2])
      E += abs(cent[k][3]- new_cent[k][3])
      E += abs(cent[k][4]- new_cent[k][4])
    if np.all(new_cent == cent) | (iter==10) | (E <=15):
      break
    else:
      cent = new_cent.copy()
      for cl in cluster_lst:
         cl.clear()
  # setting each pixel to its respective avg cluster color
  for gi in range(len(cluster_lst)):
    for pix in cluster_lst[gi]:
      py,px,_,_ = pix
      img.itemset((py,px, 0), cent[gi][2])
      img.itemset((py,px, 1), cent[gi][3])
      img.itemset((py,px, 2), cent[gi][4])
  return img
def SLIC(image, S=50):
  height = image.shape[0]
  width = image.shape[1]
  # initializing centroids in middle of 50x50 blocks
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centroids_coords = []
for y in range(S//2, height, S):
  for x in range(S//2, width, S):
    centroids_coords.append([y, x, image.item(y, x, 0),
                   image.item(y, x, 1), image.item(y, x, 2)])
# compute bgr gradients and move centroids to the smallest gradient
hsob = [[1, 2, 1],
    [0, 0, 0],
    [-1, -2, -1]]
vsob = [[1, 0, -1],
    [2, 0, -2],
    [1, 0, -1]
# skipped sqrt in B/G/R_comb because will be squared later
B_x = filter(image[:, :, 0], hsob, 3, 0)
B_y = filter(image[:, :, 0], vsob, 3, 0)
B_{comb} = np.power(B_x, 2.0) + np.power(B_y, 2.0)
G_x = filter(image[:, :, 1], hsob, 3, 1)
G_y = filter(image[:, :, 1], vsob, 3, 1)
G_{comb} = np.power(G_x, 2.0) + np.power(G_y, 2.0)
R_x = filter(image[:, :, 2], hsob, 3, 2)
R_y = filter(image[:, :, 2], vsob, 3, 2)
R_{comb} = np.power(R_x, 2.0) + np.power(R_y, 2.0)
combined = B_comb + G_comb + R_comb
# in the 3x3 windows surrounding center, finds smallest gradient
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for b in range(S//2, height, S):
    for a in range(S//2, width, S):
      index = (a//S) + ((b//S)*(width//S))
      small\_temp = -1
      for t in range(b-1,b+2):
        for u in range(a-1, a+2):
          cur_grad = combined.item(t, u)
          if (cur_grad < small_temp) | (small_temp < 0):</pre>
             small_temp = cur_grad
             centroids_coords[index] = [
               t, u, image.item(t, u, 0), image.item(t, u, 1), image.item(t, u, 2)]
  # use centroids as start for 5d kmeans
  kmeans5d = kmeans_5d(image, centroids_coords, S)
  return kmeans5d
if __name__ == '__main__':
  # k means segamnetation (part 1)
  wt image = cv2.imread("white-tower.png", cv2.IMREAD COLOR)
  seg_result = kmeans(wt_image, 10)
  cv2.imwrite('kmeans.png', seg_result)
  # # SLIC (part 2)
  slic_image = cv2.imread("wt_slic.png", cv2.IMREAD_COLOR)
  slic_res = SLIC(slic_image, 50)
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cv2.imwrite('slic.png', slic_res)

K-means Segmentation:

The k-means algorithm starts by randomly selecting pixels in the photo, extracting its RGB values, and making sure the other values do not coincide with other initial values. This is done to ensure that the initial seeds are within the photo's color scheme. The program then iterates through the photo and decides which cluster is closest (in RGB values) to each pixel's values. After the photo is processed, each cluster finds the average RGB value. If the old cluster means match the new means, the loop terminates; otherwise, the process is repeated. This was done in order to ensure that the resulting images would be consistent in respect to the colors

As shown from the photos, the same algorithm results in slightly different photos due to its random nature. Due to the random nature, the runtimes vary greatly such as the first photo taking 7 iterations, whereas the second photo took 23 iterations.



SLIC:

The concept behind SLIC is simple, but efficiently implementing it was tricky to handle. Following the algorithm outline from the assignment, centroids were instantiated at the centers of 50x50 blocks. These are later moved to the neighboring pixel with the smallest gradient in all color channels (RGB). The k-means part of the algorithm was modified to take in account of pixel distance and the RBG values. Additionally, once cluster means were decided, I chose to stick with the mean y,x,r,g,b values as opposed to y,x, img(y,x)'s rgb values because it produced stable mean values.

The following is the result of S=50, averaging all the values...



The following is the result of S=50, keeping the mean xy's rgb values...





The image to the left is the result of S=250.

From the article introducing the SLIC algorithm (link), on page 3, there is a high level implementation of it. I did attempt to replicate it, but even with S=150, the algorithm was too slow to process in a timely manner. (This code is in the zip under hw2_fail.py)

To make the process faster, the photo was iterated, identified which cluster centers were close to the pixel, and 5d Euclidean distance allowed the program to make a final decision on which cluster to go into.