# ECE 271A - Homework assignment

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## 1 Problem Formulation

- Note: Homework implemented in MATLAB 2019b.
- Goal: Segment the image into the cheetah (foreground) and grass (background).

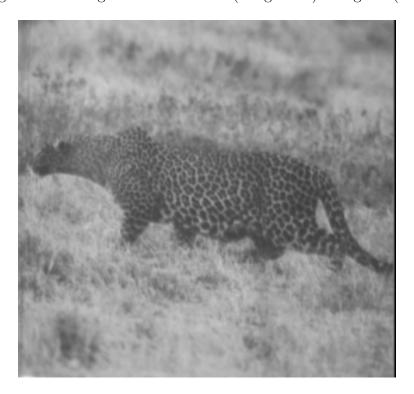


Figure 1: Cheetah in the Savannah

#### • Problem Setup as Pattern Recognition:

- Observation Space: Images as a collection of 8×8 blocks.
- Feature Computation:
  - \* For each block compute the 2D Discrete Cosine Transform.
  - \* Reorder the 8×8 frequency decomposition into Zig-Zag pattern.

- \* Resize the  $8\times8$  array into 64D vector.
- \* Compute the index of the coefficient with 2nd largest energy value.
- \* This is done as the cheetah and the grass have different textures and using their frequency decomposition they're better separated in the frequency domain.

#### • Probability Computation: Part (a) and (b)

- Class Probability: Pr(cheetah) & Pr(grass)
  - \* These values are estimated from the TrainingSamplesDCT\_8.mat dataset.
  - \* The training dataset is taken from an image similar to the test dataset.
  - \* This means that the relative distribution of the grass versus the cheetah is based on their relative presence in the training date.
  - \* Hence, the relative number of values for each class is a measure of the chance of an image block belonging to that class.
  - \* This can be computed using the dimensions TrainingSamplesCD\_8.mat
  - \* The number of training examples for the Cheetah and Grass are 250 and 1053, respectively.
  - \* Based on these dimensions Pr(cheetah) = 0.1919 & Pr(grass) = 0.8081.
- Class Conditional Densities:  $Pr(x \mid cheetah) \& Pr(x \mid grass)$ 
  - \* For each block present in the image:
  - \* The index of the second highest DCT component is used as the scalar feature.
  - \* The indexes for all the training set vectors are used to compute the histogram.
  - \* The histogram is normalized to obtain conditional distribution.
  - \* This done directly using **Histogram** function in MATLAB.

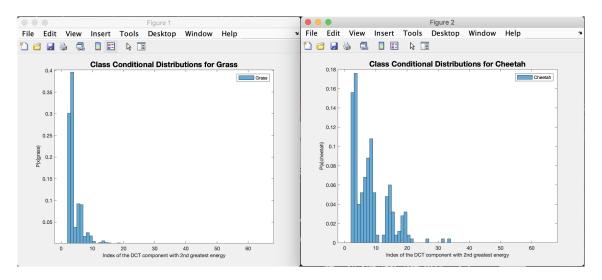


Figure 2: Class Conditional Densities:  $Pr(x \mid y)$ 

#### • Assumptions for Inferencing:

- The input image is zeropadded to obtain a segmentation map with same dimensions as input image, i.e.,  $255\times270$ .
- The image is traversed in the form of a  $8\times8$  sliding window.
- Feature x (index of the DCT coefficient with 2nd greatest energy) computed after ensuring that the coefficients are in the zig-zag order.
- Each pixel prediction is based on the feature computation with the 8×8 starting with the being the Top-Left pixel of the window.
- For each pixel then the problem boils down to a Binary Classification problem.
- Assuming there is no loss associated with the correct decision and the misclassification loss is same for both classes.

#### • Posterior Probability: Part (c) - $Pr(cheetah \mid x) \& Pr(grass \mid x)$

- For each  $8\times8$  block in the **cheetah.bmp** we compute the feature x.
- $Pr(cheetah \mid x) = \frac{Pr(x \mid cheetah) Pr(cheetah)}{Pr(x)}$
- $\Pr(grass \mid x) = \frac{\Pr(x \mid grass) \Pr(grass)}{\Pr(x)}$
- We compute the ratio  $\frac{\Pr(cheetah \mid x)}{\Pr(grass \mid x)} = \frac{\Pr(x \mid cheetah) \Pr(cheetah)}{\Pr(x \mid grass) \Pr(grass)}$
- If the ratio is greater than the threshold, i.e., 1 then we classify it as a the *Cheetah* (foreground) else we classify as it *Grass* (background).
- Basically for each feature x we look up the value in the class conditional distribution and multiply it with the prior and compare with the threshold.

### 2 Results

#### • Computing the Probability of Error

- By comparing the pixel-wise mismatches between the ground truth and the generated segmentation map the error is computed.
- Average probability of error is  $R^* = \int P_{X,Y}(x, y \neq g^*(x)) dx$ .
- Let cheetah = 1 and grass = 0,
- The above equation boils down to  $P_{error} = P(y \neq g(x))$
- $-P_{error} = P(y=1)P(g(x)=0|y=1) + P(y=0)P(g(x)=1|y=0).$
- This is basically the number of pixels mismatching between the predicted output and ground truth divided by the total number of pixels.
- The probability of error is 0.1726

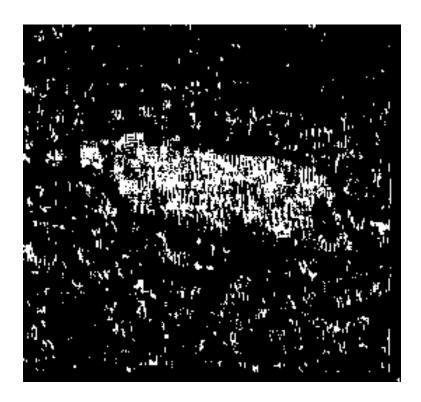


Figure 3: Resulting Segmentation Map



Figure 4: Ground Truth Segmentation Map

## 3 Appendix

#### Listing 1: MATLAB Solution Script

```
1 %% Clear workspace and close windows
3 clc
4 clear
5 close all
7
  %% Load training dataset
       DCT = load('TrainingSamplesDCT_8.mat');
9
       Train_DCT_FG = DCT.TrainsampleDCT_FG;
10
       Train_DCT_BG = DCT.TrainsampleDCT_BG;
11
12
  %% The class priors for FG and BG are computed
     Section A
14
15
       % Assuming prior distribution is (# of samples of A)/total training ...
16
       TotalNumberOfTraining_samples = size(Train_DCT_FG,1) + ...
          size(Train_DCT_BG, 1);
       FG_prior = size(Train_DCT_FG,1)/TotalNumberOfTraining_samples
       BG_prior = size(Train_DCT_BG,1)/TotalNumberOfTraining_samples
19
  %% Training data used for computing and plotting index histograms.
21
     P(x | cheetah) and P(x | grass) are the class conditionals for FG and BG.
     The feature is the index of DCT component with second largest magnitude.
23
     The feature is the index of the DCT component with 2nd greatest energy.
24
       % Feature computation for BG sections
25
           X_BG = zeros(size(Train_DCT_BG,1),1);
26
           for idx = 1:size(Train_DCT_BG, 1)
27
28
               X_BG(idx) = Index2ndLargest(Train_DCT_BG(idx,:));
29
           end
30
       % Feature computation for FG sections
31
           X_FG = zeros(size(Train_DCT_FG,1),1);
32
           for idx = 1:size(Train_DCT_FG,1)
               X_FG(idx) = Index2ndLargest(Train_DCT_FG(idx,:));
34
           end
36
       % Histogram plotting for both BG and FG
37
       % The bins for the histograms
38
39
           edges = 1:65;
           fontSize = 10;
40
41
           figure(1)
42
43
           h_BG = histogram(X_BG, 'BinEdges', edges, 'normalization', ...
44
               'pdf', 'DisplayName', 'BG');
           BG_CCD = histcounts(X_BG, 'BinEdges', edges, 'Normalization', ...
45
               'probability');
46
           title('Class Conditional Distributions for Grass', 'FontSize', ...
47
               1.5*fontSize);
```

```
xlabel('Index of the DCT component with 2nd greatest energy', ...
               'FontSize', fontSize);
           ylabel('P(x|grass)', 'FontSize', fontSize);
49
           legend('Grass')
50
51
           figure(2)
52
53
           h_FG = histogram(X_FG, 'BinEdges', edges, 'normalization', ...
54
               'pdf', 'DisplayName', 'FG');
           FG_CCD = histcounts(X_FG, 'BinEdges', edges, 'Normalization', ...
55
               'probability');
           title('Class Conditional Distributions for Cheetah', ...
57
               'FontSize', 1.5*fontSize);
           xlabel('Index of the DCT component with 2nd greatest energy', ...
58
               'FontSize', fontSize);
           ylabel('P(x|cheetah)', 'FontSize', fontSize);
59
           legend('Cheetah')
61
  %% For each block in the image cheetah.bmp, compute the feature X and ...
      state variable Y.
  % For Y use the minimum probability of error rule based on the ...
      distributions obtained above.
     Store the state in an array A and then convert to binary image using ...
      imagesc and colormap(gray(255))
65
       block\_size = 8;
66
67
       % Read the ZigZag pattern and convert to array and index from 1
68
           ZigZagPattern = table2array(readtable('Zig-Zag Pattern.txt'))+1;
69
70
       % Read image and convert to double
71
           image = im2double(imread('cheetah.bmp'));
72
73
       % Reading image dimensions
74
           [height, width] = size(image);
75
           [h_8, w_8] = deal(8*(ceil(height/8)+1), 8*(ceil(width/8)+1));
77
       % Zeropad the image and convert to 8x8
78
           zeropad = zeros(h_8, w_8);
79
           zeropad(1:height,1:width) = image;
80
81
       % Create a blank array X
82
           X = zeros(height, width);
83
           dctZigZag = zeros(1,block_size*block_size);
84
85
       % Iterating through the image in 8x8 blocks through a sliding window
86
       for h = 1:height
87
           for w = 1: width
88
89
               dctBlock = dct2(zeropad(h:h+block_size-1,w:w+block_size-1));
90
91
               % Rearranging the DCT Components in ZigZag Patterned Vector
92
               for i = 1:block_size
93
```

```
for j = 1:block_size
                         dctZigZag(ZigZagPattern(i,j)) = dctBlock(i,j);
95
                    end
96
                end
97
98
                % Computing the feature for the block
aa
100
                X(h,w) = Index2ndLargest(dctZiqZaq);
101
102
            end
       end
103
104
105
       % Computing the Posteriori distributions for generating predictions
106
       BG_posteriori = BG_CCD(X) *BG_prior;
       FG_posteriori = FG_CCD(X)*FG_prior;
107
       A = FG_posteriori > BG_posteriori;
108
109
110
       figure (3)
111
       imagesc(A);
       colormap(gray(255));
112
       imwrite(A, 'result.bmp');
113
       title('Predicted Segmentation based on Bayesian Decision Theory', ...
114
           'FontSize', 1.5*fontSize);
115
116
   \% Compare the ground truth in image cheetah_mask.bmp and compute the \dots
117
       probability of error
118
119
       % Read the ground truth image
            ground_truth = im2double(imread('cheetah_mask.bmp'));
120
121
       % Probability of error for Cheetah pixels misclassified as Grass
122
            probability_error_cheetah = sum(ground_truth & ¬...
123
               A, 'all') / sum (ground_truth, 'all');
        % Probability of error for Grass pixels misclassified as Cheetah
124
            probability_error_grass = sum(¬ground_truth & ...
125
                A, 'all')/sum(¬ground_truth, 'all');
126
            probability_error = (FG_prior*probability_error_cheetah) + ...
127
                (BG_prior*probability_error_grass)
128
   %% UTILITY FUNCTIONS
129
        % 1. Index2ndLargest
130
       % Find Index of the second coefficient with second largest magnitude
131
       % Much faster than sorting and finding value at second position
132
133
134
        function [ind2] = Index2ndLargest(FeatureVector) % i is the ...
           x-largest value
            absFeatureVector = abs(FeatureVector);
135
136
            [\neg, ind1] = max(absFeatureVector);
            absFeatureVector(ind1) = -Inf;
137
            [\neg, ind2] = max(absFeatureVector);
138
139
       end
```