

Figure 1: Dataset 1/strategy 1 percent error vs log(alpha) for predictive equation

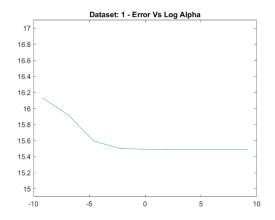


Figure 2: Dataset 1/strategy 2 percent error vs log(alpha) for predictive equation

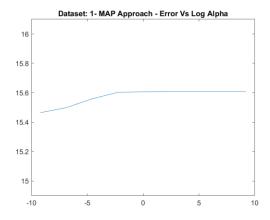


Figure 3: Dataset 1/strategy 1 percent error vs log(alpha) for MAP approach

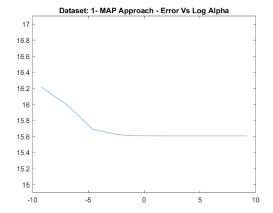


Figure 4: Dataset 1/strategy 2 percent error vs log(alpha) for MAP approach

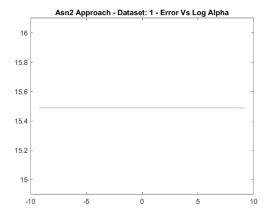


Figure 5: Dataset 1/strategy 1 percent error vs log(alpha) for ML approach

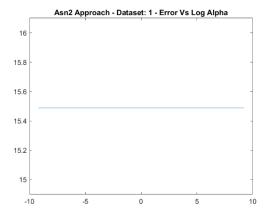


Figure 6: Dataset 1/strategy 2 percent error vs log(alpha) for ML approach

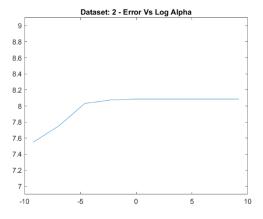


Figure 7: Dataset 2/strategy 1 percent error vs log(alpha) for predictive equation

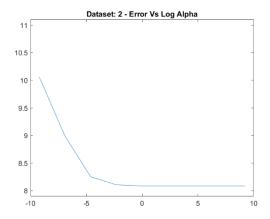


Figure 8: Dataset 2/strategy 2 percent error vs log(alpha) for predictive equation

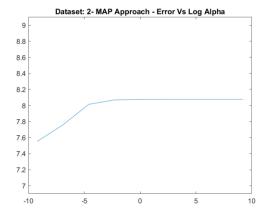


Figure 9: Dataset 2/strategy 1 percent error vs log(alpha) for MAP approach

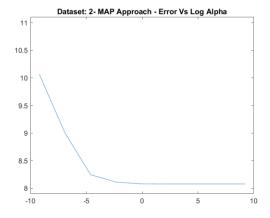


Figure 10: Dataset 2/strategy 2 percent error vs log(alpha) for MAP approach

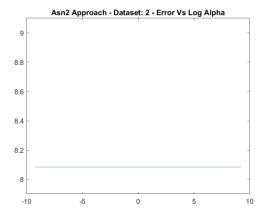


Figure 11: Dataset 2/strategy 1 percent error vs log(alpha) for ML approach

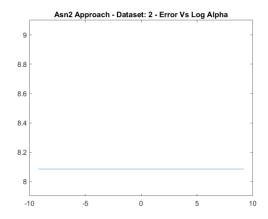


Figure 12: Dataset 2/strategy 2 percent error vs log(alpha) for ML approach

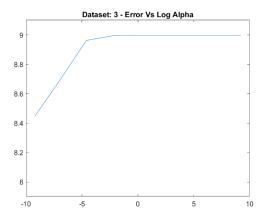


Figure 13: Dataset 3/strategy 1 percent error vs log(alpha) for predictive equation

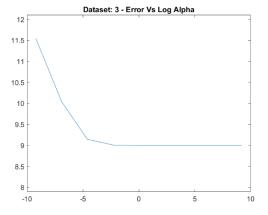


Figure 14: Dataset 3/strategy 2 percent error vs log(alpha) for predictive equation

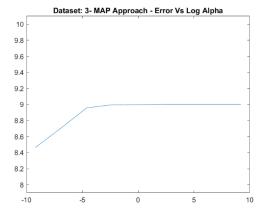


Figure 15: Dataset 3/strategy 1 percent error vs log(alpha) for MAP approach

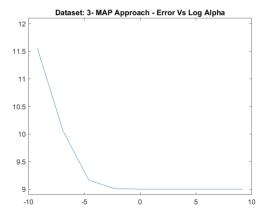


Figure 16: Dataset 3/strategy 2 percent error vs log(alpha) for MAP approach

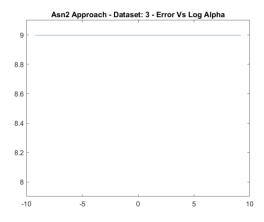


Figure 17: Dataset 3/strategy 1 percent error vs log(alpha) for ML approach

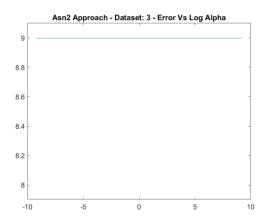


Figure 18: Dataset 3/strategy 2 percent error vs log(alpha) for ML approach

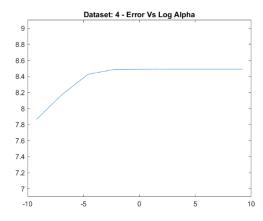


Figure 19: Dataset 4/strategy 1 percent error vs log(alpha) for predictive equation

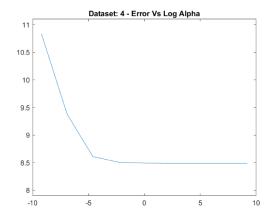


Figure 20: Dataset 4/strategy 2 percent error vs log(alpha) for predictive equation

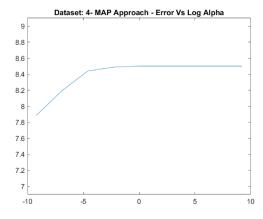


Figure 21: Dataset 4/strategy 1 percent error vs log(alpha) for MAP approach

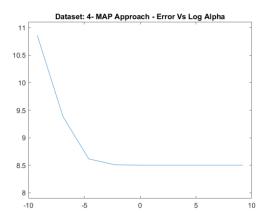


Figure 22: Dataset 4/strategy 2 percent error vs log(alpha) for MAP approach

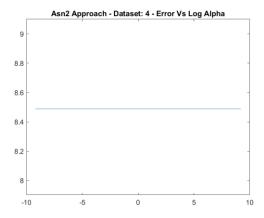


Figure 23: Dataset 4/strategy 1 percent error vs log(alpha) for ML approach

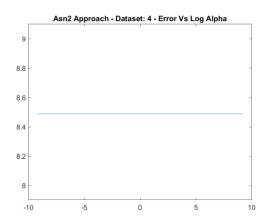


Figure 24: Dataset 4/strategy 2 percent error vs log(alpha) for ML approach

Analysis

All the curves for the predictive equation and MAP approaches are asymptotic, and the "curves" for the ML approach are linear (as the function for ML is not dependent on alpha). For strategy 1, as alpha increases the error percentage increases toward an upper limit. For strategy 2, as alpha increases the error percentage decreases toward a lower limit. These upper and lower limits, however, are equivalent (i.e. strategy 1 increases toward the limit, whereas strategy 2 decreases toward that same limit value). This limit value, spanning all datasets (with one exception) and strategy types is the error percentage calculated by the ML approach. The one exception to this trend is observed in dataset 1. In dataset 1 (for both strategies) the MAP approach tends toward an asymptote of approximately 15.6, whereas the predictive equation approach tends toward an asymptote of approximately 15.5. The ML approach has an error percentage of approximately 15.5. From this observation, it seems as if the MAP approach will result in a larger percentage of error relative to the predictive equation approach when the dataset is small*. As the dataset size increases (dataset 2, 3, and 4 are all larger than dataset 1), however, both the MAP and predictive equation approaches approach the same asymptote value – this asymptote value is the value of the ML percentage of error.

^{*}Small in this case is 300 DCT coefficient arrays for the background and 75 DCT coefficient arrays for the foreground.

Code

```
%Joseph Bell
%ECE271A HW3 and 4
clc;
clear;
load('TrainingSamplesDCT subsets 8.mat');
load('Alpha.mat');
%%%% Starting off with Data Set 1 and strategy 1%%%%%
% Strategy 1 = ?0 is smaller for the (darker) cheetah class (?0 = 1)
% and larger for the (lighter) grass class (?0 = 3)
%%%%% Part a %%%%%
%load('Prior 1.mat'); %priors for strategy 1 - consists of weights, mu0 FG,
                    %and mu0 BG
load('Prior 2.mat'); %priors for strategy 2 - consists of weights, mu0 FG,
                    %and mu0 BG
% Reading in cheetah image and mask
cheetah img = imread('cheetah.bmp');
cheetah img = im2double(cheetah img); %converting to double values since training data
is of type double
cheetah mask = imread('cheetah mask.bmp');
cheetah mask = im2double(cheetah mask);
[cheetah rows, cheetah cols] = size(cheetah img);
cheetah img = cheetah img(1:8*floor(cheetah rows/8),1:8*floor(cheetah cols/8));
%modifying image so it can be split into 8x8 blocks
[cheetah rows, cheetah cols] = size(cheetah img); %overwriting for modified dimensions
%%%%%% STARTING LOOP %%%%%%%%% Loops 4 times due to 4 data sets
$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$$
for d=1:4
   alpha_values = []; %array of alpha values used for plotting
   error percentages = []; %array of error percentages per alpha used for plotting
   dataset FG = []; %stores selected foreground data set
   dataset BG = []; %stores selected background data set
   %%%% IF/ELSEIF for selecting data set to operate on
   if d == 1
```

```
dataset FG = D1 FG;
       dataset BG = D1 BG;
   elseif d == 2
       dataset FG = D2 FG;
       dataset_BG = D2_BG;
   elseif d == 3
       dataset FG = D3 FG;
       dataset BG = D3 BG;
   elseif d == 4
       dataset FG = D4 FG;
       dataset BG = D4 BG;
   end
    %Taking rows and cols used for calculations
    [data rows FG, data cols FG] = size(dataset FG);
    [data_rows_BG, data_cols_BG] = size(dataset_BG);
   %zig zag scanning of data to order coefficents from 1-64
   %1 row per DC coefficient (First row should have largest values)
   cheetah zigzag = zeros(64, data rows FG);
   grass_zigzag = zeros(64, data_rows_BG);
   %Credit to Alexey Sokolov from
https://www.mathworks.com/matlabcentral/fileexchange/15317-zigzag-scan
   %for the zig zag code
   %Reading into zig zag and transposing to create n*64 matrix
   for row=1:data rows FG
       cheetah_zigzag(:,row) = zigzag(dataset_FG(row,:));
   end
    for row=1:data rows BG
       grass_zigzag(:,row) = zigzag(dataset_BG(row,:));
   end
   means_variance_cheetah = zeros(64, 1, 2); %(:,:,1) = mean
   means variance grass = zeros(64, 1, 2); %(:,:,2) = variance
    % Calculating mean and variance of each coefficient
    % CODE COPIED FROM MY ASSIGNMENT 2
    %cheetah loop
   for row=1:data_cols_FG
       N = data rows FG;
       sample mean = 0;
       sample_variance = 0;
       sample = cheetah zigzag(row,:); %grab each coefficient row
       for i=1:N
```

```
sample mean = sample mean + sample (1, i);
    end
    sample_mean = sample_mean/N;
    for i=1:N
        sample variance = sample variance + (sample(1,i) - sample mean)^2;
   sample variance = sample variance/N;
   means variance cheetah(row,1,1) = sample mean;
   means variance cheetah(row,1,2) = sample variance;
end
%grass loop
for row=1:data cols BG
   N = data_rows_BG;
   sample_mean = 0;
   sample variance = 0;
   sample = grass zigzag(row,:); %grab each coefficient row
   for i=1:N
       sample_mean = sample_mean + sample(1,i);
    sample mean = sample mean/N;
    for i=1:N
       sample variance = sample variance + (sample(1,i) - sample mean)^2;
   sample_variance = sample_variance/N;
   means variance grass(row,1,1) = sample mean;
   means variance grass(row, 1, 2) = sample variance;
end
% Calculating covariance matrices for foreground (cheetah)
% and background (grass)
% CODE COPIED FROM MY ASSIGNMENT 2
cheetah_covariances = zeros(64,64);
grass covariances = zeros(64,64);
%calculating covariance matrix for cheetah
for i=1:64
   p1 = cheetah zigzag(i,:); %grab coefficient row
   mu 1 = means variance cheetah(i,1,1);
    for j=1:64
       p2 = cheetah_zigzag(j,:); %grab coefficient row
       mu 2 = means variance cheetah(j,1,1);
       temp = 0;
       for k=1:data_rows_FG
```

```
temp = temp + (p1(1,k) - mu 1)*(p2(1,k) - mu 2);
       end
       cheetah covariances(i,j) = temp/data rows FG;
   end
end
%calculating covariance matrix for grass
for i=1:64
   p1 = grass zigzag(i,:); %grab coefficient row
   mu 1 = means variance grass(i,1,1);
   for j=1:64
       p2 = grass zigzag(j,:); %grab coefficient row
       mu_2 = means_variance_grass(j,1,1);
       temp = 0;
       for k=1:data rows BG
           temp = temp + (p1(1,k) - mu_1)*(p2(1,k) - mu_2);
       grass_covariances(i,j) = temp/data_rows_BG;
   end
end
%Used for probability calculations
mu n hat cheetah1 = zeros(1,64);
mu n hat grass1 = zeros(1,64);
mu n cheetah1 = zeros(1,64);
mu_n_grass1 = zeros(1,64);
%Used for MAP part
prior cheetah = data rows FG/(data rows FG + data rows BG);
prior grass = data rows BG/(data rows BG+data rows FG);
%%%%% Calculating mu n hat values %%%%
for i=1:64
   for j=1:data rows FG
       mu n hat cheetahl(1,i) = mu n hat cheetahl(1,i) + dataset FG(j,i);
   mu n hat cheetahl(1,i) = mu n hat cheetahl(1,i)/data rows FG;
end
for i=1:64
   for j=1:data rows BG
       mu n hat grass1(1,i) = mu n hat <math>grass1(1,i) + dataset BG(j,i);
   mu_n_hat_grass1(1,i) = mu_n_hat_grass1(1,i)/data_rows_BG;
end
%%%%% STARTING LOOP FOR ALPHA %%%%%
```

```
for a=1:9
       new image = zeros(cheetah rows, cheetah cols); %Returned image
       %Values used for calculations%
       sigma 1 = alpha(1,a)*diag(W0);
       mu n cheetah1 = sigma 1 * inv(sigma 1 +
1/data rows FG*cheetah covariances)*transpose(mu n hat cheetah1) +
1/data rows FG*cheetah covariances*inv(sigma 1+1/data rows FG*cheetah covariances)*tra
nspose(mu0 FG);
       mu n grass1 = sigma 1 * inv(sigma 1 +
1/data rows BG*grass covariances) *transpose(mu n hat grass1) +
1/data rows BG*grass covariances*inv(sigma 1+1/data rows BG*grass covariances)*transpo
se(mu0 BG);
        sigma_n_cheetah = sigma_1*inv(sigma_1 +
1/data rows FG*cheetah covariances) *1/data rows FG*cheetah covariances;
        sigma n grass = sigma 1*inv(sigma 1 +
1/data rows BG*grass covariances) *1/data rows BG*grass covariances;
        sigma cheetah total = cheetah covariances + sigma n cheetah;
       sigma_grass_total = grass_covariances + sigma_n_grass;
       %Multivariate Gaussian Distribution PDF functions for part a
        fun_cheetah = @(x) 1/sqrt((det(sigma_cheetah_total)*(2*pi)^64))*exp(-
1/2*transpose(x-mu_n_cheetah1)*inv(sigma_cheetah_total)*(x-mu_n_cheetah1));
        fun grass= @(x) 1/sgrt((det(sigma grass total)*(2*pi)^64))*exp(-
1/2*transpose(x-mu n grass1)*inv(sigma grass total)*(x-mu n grass1));
        for i=1:cheetah cols-7 %shift scan pointer over a column
           for j=1:cheetah rows-7
               block = cheetah img(j:7+j,i:7+i); %grab 8x8 block
               block dct = dct2(block);
               zzblock dct = transpose(zigzag(block dct));
               P x D cheetah = fun cheetah(zzblock dct);
               P x D grass = fun grass(zzblock dct);
               if P x D cheetah * prior cheetah > P x D grass * prior grass
                   new image(j:j,i:i) = 1;
               end
           end
        f = figure() % Returning image per alpha
       imagesc(new_image);
       colormap(gray(255));
       title(['Dataset: ', num2str(d),' - Alpha: ', num2str(alpha(1,a))])
       saveas(f,[pwd,'/results/D_',num2str(d),'_A_',num2str(a),'.png']);
       %%%%% Calculating percent error for part a Alpha values %%%%%
```

```
counter correct = 0;
   total pixels = cheetah rows*cheetah cols;
   for i=1:cheetah rows
       for j=1:cheetah cols
           if cheetah mask(i,j) == new image(i,j)
               counter correct = counter correct + 1;
           end
       end
   percent correct = counter correct/total pixels*100;
   error_percentage = 100 - percent_correct;
   alpha values = [alpha values log(alpha(1,a))];
   error percentages = [error percentages error percentage];
end% END OF a=1:9 Still in d data set loop
f = figure() %plotting percent error vs alpha
plot(alpha values, error percentages);
ylim([floor(min(error percentages))-0.1 ceil(max(error percentages))+0.1])
title(['Dataset: ', num2str(d), ' - Error Vs Log Alpha']);
saveas(f,[pwd,'/results/error plot D ',num2str(d),'.png']);
% Starting loop of alphas for assignment 2 approach
%calculating MLE covariance matrix for cheetah
cheetah covariances MLE = zeros(64,64);
grass covariances MLE = zeros(64,64);
   p1 = cheetah zigzag(i,:); %grab coefficient row
   mu 1 = means variance cheetah(i,1,1);
   for j=1:64
       p2 = cheetah zigzag(j,:); %grab coefficient row
       mu 2 = means variance cheetah(j,1,1);
       temp = 0;
       for k=1:data rows FG
           temp = temp + (p1(1,k) - mu 1)*(p2(1,k) - mu 2);
       cheetah covariances MLE(i,j) = temp/(data rows FG-1);
   end
end
%calculating covariance matrix for grass
for i=1:64
   p1 = grass_zigzag(i,:); %grab coefficient row
   mu_1 = means_variance_grass(i,1,1);
   for j=1:64
       p2 = grass zigzag(j,:); %grab coefficient row
       mu_2 = means_variance_grass(j,1,1);
```

```
temp = 0;
                           for k=1:data rows BG
                                   temp = temp + (p1(1,k) - mu_1)*(p2(1,k) - mu_2);
                           grass covariances MLE(i,j) = temp/(data rows BG-1);
                 end
        end
        alpha values Asn2 = []; %array of alpha values used for plotting
        error_percentages_Asn2 = []; %array of error percentages per alpha used for
plotting
         for a=1:9
                 new_image2 = zeros(cheetah_rows, cheetah_cols);
                 fun\_cheetah\_Asn2 = @(x) 1/sqrt((det(cheetah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64))*exp(-detah\_covariances\_MLE)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(2*pi)^64)*(
1/2*transpose(x-means variance cheetah(:,:,1))*inv(cheetah covariances MLE)*(x-
means variance cheetah(:,:,1)));
                  fun_grass_Asn2= @(x) 1/sqrt((det(grass_covariances_MLE)*(2*pi)^64))*exp(-
1/2*transpose(x-means_variance_grass(:,:,1))*inv(grass_covariances_MLE)*(x-
means_variance_grass(:,:,1)));
                 for i=1:cheetah cols-7 %shift scan pointer over a column
                           for j=1:cheetah rows-7
                                   block = cheetah img(j:7+j,i:7+i); %grab 8x8 block
                                   block dct = dct2(block);
                                   zzblock_dct = transpose(zigzag(block_dct));
                                   P x y cheetah = fun cheetah Asn2(zzblock dct);
                                   P_x_y_grass = fun_grass_Asn2(zzblock_dct);
                                   if P_x_y_cheetah * prior_cheetah > P_x_y_grass * prior_grass
                                                      new image2(j:j,i:i) = 1;
                                    end
                           end
                 end
                 %Calculating percent error of assignment 2 method
                 counter correct Asn2 = 0;
                 total pixels = cheetah rows*cheetah cols;
                  for i=1:cheetah rows
                           for j=1:cheetah cols
                                   if cheetah mask(i,j) == new image2(i,j)
                                             counter correct Asn2 = counter correct Asn2 + 1;
                                   end
                           end
                 percent_correct_Asn2 = counter_correct_Asn2/total_pixels*100;
                 error percentage Asn2 = 100 - percent correct Asn2;
                 alpha_values_Asn2 = [alpha_values_Asn2 log(alpha(1,a))];
                 error percentages Asn2 = [error percentages Asn2 error percentage Asn2];
         end%END OF a=1:9 for Assignment 2 MLE method
```

```
f = figure() %plotting assignment 2 method (1 per data set just plotting last one
they're all the same)
  imagesc(new image2); %as I'm not multiplying covariace by alpha for this part
only using MLE
  colormap(gray(255)); %percent error chart should be a horizontal line
   title(['Dataset: ', num2str(d), ' - Assignment 2 Method'])
   saveas(f,[pwd,'/results/Asn2 D ',num2str(d),'.png']);
   f = figure() %plotting percent error vs alpha (should only be 4 of these)
   plot(alpha values Asn2, error percentages Asn2);
   ylim([floor(min(error percentages Asn2))-0.1
ceil(max(error percentages Asn2))+0.1])
   title(['Asn2 Approach - Dataset: ', num2str(d), ' - Error Vs Log Alpha']);
   saveas(f,[pwd,'/results/error plot Asn2 D ',num2str(d),'.png']);
   alpha values = []; %Stores alpha values for plotting
   error percentages = []; %Stores error percentage per alpha
   %Same stuff except using MAP for mu
   for a=1:9
      new image = zeros(cheetah rows, cheetah cols);
       sigma 1 = alpha(1,a)*diag(W0);
       mu_n_cheetah1 = sigma_1 * inv(sigma_1 +
1/data rows FG*cheetah covariances) *transpose(mu n hat cheetah1) +
1/data rows FG*cheetah covariances*inv(sigma 1+1/data rows FG*cheetah covariances)*tra
nspose(mu0 FG);
       mu_n_grass1 = sigma_1 * inv(sigma_1 +
1/data rows BG*grass covariances)*transpose(mu n hat grass1) +
1/data rows BG*grass covariances*inv(sigma 1+1/data rows BG*grass covariances)*transpo
se(mu0 BG);;
       %sigma n cheetah = sigma 1*inv(sigma 1 +
1/data rows FG*cheetah covariances) *1/data rows FG*cheetah covariances;
       %sigma n grass = sigma 1*inv(sigma 1 +
1/data rows BG*grass covariances) *1/data rows BG*grass covariances;
       sigma n cheetah = 0;
       sigma n grass = 0;
       sigma_cheetah_total = cheetah_covariances + sigma_n_cheetah;
       sigma grass total = grass covariances + sigma n grass;
```

```
fun cheetah D1c = @(x) 1/sqrt((det(sigma cheetah total)*(2*pi)^64))*exp(-
1/2*transpose(x-mu n cheetah1)*inv(sigma cheetah total)*(x-mu n cheetah1));
        fun grass D1c= @(x) 1/sqrt((det(sigma grass total)*(2*pi)^64))*exp(-
1/2*transpose(x-mu n grass1)*inv(sigma grass total)*(x-mu n grass1));
        for i=1:cheetah cols-7 %shift scan pointer over a column
            for j=1:cheetah rows-7
                block = cheetah img(j:7+j,i:7+i); %grab 8x8 block
                block dct = dct2(block);
                zzblock dct = transpose(zigzag(block dct));
                P x D cheetah = fun cheetah D1c(zzblock dct);
                P_x_D_grass = fun_grass_D1c(zzblock_dct);
                if P x D cheetah * prior cheetah > P x D grass * prior grass
                    new_image(j:j,i:i) = 1;
                end
            end
        end
        f = figure()%Plotting per alpha for MAP approach
        imagesc(new image);
        colormap(gray(255));
        title(['Dataset: ', num2str(d), ' - MAP Approach - Alpha: ',
num2str(alpha(1,a))])
        saveas(f,[pwd,'/results/MAP D ',num2str(d),' A ',num2str(a),'.png']);
        %Calculating percent error for alpha and MAP approach
        counter correct = 0;
        total pixels = cheetah rows*cheetah cols;
        for i=1:cheetah rows
            for j=1:cheetah cols
                if cheetah_mask(i,j) == new_image(i,j)
                    counter correct = counter correct + 1;
                end
            end
        percent correct = counter correct/total pixels*100;
        error percentage = 100 - percent correct;
        alpha values = [alpha values log(alpha(1,a))];
        error percentages = [error percentages error percentage];
    end
    f = figure()%Potting percent error vs alpha values for MAP
    plot(alpha values, error percentages);
    ylim([floor(min(error percentages))-0.1 ceil(max(error percentages))+0.1])
    title(['Dataset: ', num2str(d), '- MAP Approach', ' - Error Vs Log Alpha']);
    saveas(f,[pwd,'/results/error_MAP_D',num2str(d),'.png']);
end
```