DIGITAL IMAGE PROCESSING ELL715 ASSIGNMENT 3

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Question 1

The pixels in an image are scanned from left to the right and from the top to the bottom. Each new pixel is predicted by the average of the pixel above and the one to the left. Let f and F represent the original and the predicted values, and e = f - F is the prediction error. The prediction error is quantized to "0", "B", or "-B" according to:

$$\hat{e} = \begin{cases} -B & e < -T \\ 0 & -T \le e \le T \\ B & e > T \end{cases}$$

Find the optimum weights while predicting the image such that mean square error is minimum. Repeat the process if you use all nearest neighbor to predict the pixel value. Repeat the process on any image of your choice

Solution

2-Neighbour Approach

In this approach, we utilize previously predicted pixel values from the top and left neighbors ('F[i][j-1]' and 'F[i-1][j]') while considering weights 'w1' and 'w2' to forecast the new pixel value at position '(i,j)'. The objective is to minimize the mean squared error (MSE) between the original image and the image predicted using these weighted combinations. The constraint 'w1 + w2 = 1' ensures weight normalization, resulting in a linear combination of the top and left neighbors.

4-Neighbour Approach

In this approach, we incorporate information from four neighboring pixels (above, below, left, and right) in addition to the original pixel to predict the new pixel value. We adjust the influence of these neighbors using weights 'w_above', 'w_below', 'w_left', and 'w_right'. The optimization seeks to determine optimal weights that minimize the MSE between the original image and the predicted image.

Both approaches employ a quantization function, 'quantize_error', to map prediction errors to three levels (-1, 0, 1). The optimization process aims to find weights that minimize the quantized MSE.

Optimization Process

We employ the SciPy 'minimize' function to find the optimal weights for both approaches. For the 2-neighbour approach, we optimize 'w1' and 'w2', and for the 4-neighbour approach, we optimize 'w_above', 'w_below', 'w_left', and 'w_right'. The optimization is subject to the constraint that the sum of these weights equals 1, ensuring that the prediction is a linear combination of neighboring pixels.

Python Code

```
from PIL import Image
  import numpy as np
  image_path = '/content/harry.jpg'
  image = Image.open(image_path)
  # Converting the image to grayscale
  if image.mode != 'L':
      image = image.convert('L')
10
  # Converting the grayscale image to a NumPy matrix
11
  image_matrix = np.array(image)
12
13
  print("Image Matrix Shape:", image_matrix.shape)
14
15
16
  import numpy as np
  from scipy.optimize import minimize
  import matplotlib.pyplot as plt
20
  f = image_matrix
21
22
  # Define the objective function to calculate MSE and then quantize error
23
  def calculate_mse_and_quantize(weights, original_image):
24
      w1, w2 = weights
25
      M, N = original_image.shape
26
      F = np.zeros((M, N))
27
28
      for i in range(M):
29
          for j in range(N):
30
               if i == 0 and j == 0:
31
                   F[i][j] = (int)(original_image[i][j])
32
               elif i == 0:
33
                   \# F[i][j] = w1*F[i][j-1]
34
                   F[i][j] = (int)(original_image[i][j])
35
               elif j == 0:
36
                   \# F[i][j] = w2*F[i-1][j]
                   F[i][j] = (int)(original_image[i][j])
               else:
                   F[i][j] = (int)(w1 * original_image[i][j-1] + w2 *
40
                       original_image[i-1][j])
41
      prediction_errors = original_image - F
42
```

```
flatten_array = prediction_errors.flatten()
43
       quantized_errors = np.zeros(flatten_array.size)
44
       # print(flatten_array.size)
45
       for i in range(flatten_array.size):
46
         quantized_errors[i] = quantize_error(flatten_array[i])
47
       mse = np.mean(quantized_errors**2)
48
49
      return mse, F
50
51
  # Define the quantization function for prediction errors
52
  def quantize_error(error):
53
       if error < -1:</pre>
54
          return -1
55
       elif error >= -1 and error <= 1:</pre>
56
57
          return 0
       else:
59
           return 1
  # Define the optimization objective (minimize quantized MSE)
62
  def objective(weights):
       return calculate_mse_and_quantize(weights, image_matrix)[0] # Use
63
          image\_matrix \ instead \ of \ predefined \ matrix \ f
64
  # Initial guess for weights (w1, w2)
65
  initial_weights = [0.5, 0.5]
66
  # Define bounds for weights
  bounds = [(0, 1), (0, 1)]
  # Add x1 + x2 = 1 as an equality constraint
71
  constraints = ({'type': 'eq', 'fun': lambda weights: weights[0] + weights[1] -
72
      1},)
73
  # Optimize weights to minimize quantized MSE
74
  result = minimize(objective, initial_weights, bounds=bounds,
      constraints=constraints)
76
  \# Extracting the optimized weights
78 optimized_weights = result.x
79 w1_optimized, w2_optimized = optimized_weights
  \mbox{\# Print the optimized weights and quantized MSE}
82 print("Optimized Weights (w1, w2):", optimized_weights)
  print("Optimized Quantized MSE:", result.fun)
  # Calculating the predicted image using the optimized weights
  optimal_mse, predicted_matrix = calculate_mse_and_quantize(optimized_weights,
      image_matrix)
  predicted_image = Image.fromarray(predicted_matrix)
90 # Display both the original and predicted images side by side
91 plt.figure(figsize=(12, 6))
93 # Original Image
94 plt.subplot(1, 2, 1)
95 plt.imshow(image_matrix, cmap='gray')
96 plt.title("Original Image")
98 # Predicted Image
99 plt.subplot(1, 2, 2)
plt.imshow(predicted_image, cmap='gray')
plt.title("Predicted Image")
```

```
102
  plt.show()
103
104
105
   # In the below code we tried to experiment it using the updated values to
106
       predict the new pixel values
107
   # Define the objective function to calculate MSE and then quantize error
   def calculate_mse_and_quantize(weights, original_image):
       w1, w2 = weights
110
       M, N = original_image.shape
111
       F = np.zeros((M, N))
112
113
       for i in range(M):
114
           for j in range(N):
115
                if i == 0 and j == 0:
116
                    F[i][j] = (int)(original_image[i][j])
                elif i == 0:
                    \# F[i][j] = w1*F[i][j-1]
119
120
                    F[i][j] = (int)(original_image[i][j])
                elif j == 0:
121
                    \# F[i][j] = w2*F[i-1][j]
122
                    F[i][j] = (int)(original_image[i][j])
123
124
                    F[i][j] = (int)(w1 * F[i][j-1] + w2 * F[i-1][j])
125
126
127
       prediction_errors = original_image - F
       flatten_array = prediction_errors.flatten()
128
       quantized_errors = np.zeros(flatten_array.size)
129
       # print(flatten_array.size)
130
       for i in range(flatten_array.size):
131
         quantized_errors[i] = quantize_error(flatten_array[i])
132
       mse = np.mean(quantized_errors**2)
133
134
       return mse, F
135
136
137
   # Define the quantization function for prediction errors
   def quantize_error(error):
       if error < -1:</pre>
           return -1
140
       elif error >= -1 and error <= 1:
141
           return 0
142
       else:
143
           return 1
144
145
   # Define the optimization objective
146
   def objective(weights):
147
       return calculate_mse_and_quantize(weights, image_matrix)[0] # Use
148
           image_matrix instead of predefined matrix f
149
   # Initial guess for weights (w1, w2)
150
initial_weights = [0.5, 0.5]
152
   # Define bounds for weights
153
bounds = [(0, 1), (0, 1)] # weights between 0 and 1
155
   \# Add x1 + x2 = 1 as an equality constraint
157
  constraints = ({'type': 'eq', 'fun': lambda weights: weights[0] + weights[1] -
      1},)
158
159 # Optimize weights to minimize quantized MSE
result = minimize(objective, initial_weights, bounds=bounds,
      constraints=constraints)
```

```
161
  # Extract the optimized weights
162
optimized_weights = result.x
  w1_optimized, w2_optimized = optimized_weights
164
  # print("optimized weights:", result.x)
165
166
   \# Print the optimized weights and quantized MSE
  print("Optimized Weights (w1, w2):", optimized_weights)
  print("Optimized Quantized MSE:", result.fun)
170
  \# Calculating the predicted image using the optimized weights
171
  optimal_mse, predicted_matrix = calculate_mse_and_quantize(optimized_weights,
172
      image_matrix)
173
  predicted_image = Image.fromarray(predicted_matrix)
174
175
  # Display both the original and predicted images side by side
  plt.figure(figsize=(12, 6))
178
179
  # Original Image
180
  plt.subplot(1, 2, 1)
181
  plt.imshow(image_matrix, cmap='gray')
  plt.title("Original Image")
182
183
  # Predicted Image
184
  plt.subplot(1, 2, 2)
185
  plt.imshow(predicted_image, cmap='gray')
  plt.title("Predicted Image")
  plt.show()
189
190
191
  # 4 neighbours to predict the pixel value
192
193
  def calculate_mse_and_quantize_neighbors(weights, original_image):
194
       w_above, w_below, w_left, w_right = weights
195
       M, N = original_image.shape
196
       F = np.zeros((M, N))
       for i in range(M):
           for j in range(N):
200
               if i == 0 and j == 0:
201
                    F[i][j] = original_image[i][j]
202
               elif i == 0:
203
                    \# F[i][j] = (w_left * F[i][j - 1] + original_image[i][j]) /
204
                        (w_left + 1)
                   F[i][j] = original_image[i][j]
205
                elif j == 0:
206
                    \# F[i][j] = (w_above * F[i - 1][j] + original_image[i][j]) /
                        (w_above + 1)
                   F[i][j] = original_image[i][j]
208
               else:
                    neighbors = [
210
                        w_above * original_image[i - 1][j],
                                                                     # Above
211
                        w_below * original_image[i + 1][j] if i + 1 < M else</pre>
212
                            original_image[i][j], # Below (with boundary check)
                        w_left * original_image[i][j - 1],
213
                        w_right * original_image[i][j + 1] if j + 1 < N else
214
                            original_image[i][j] # Right (with boundary check)
                    ٦
                    F[i][j] = sum(neighbors)
216
217
       prediction_errors = original_image - F
218
```

```
flatten_array = prediction_errors.flatten()
219
       quantized_errors = np.zeros(flatten_array.size)
220
       # print(flatten_array.size)
221
       for i in range(flatten_array.size):
222
         quantized_errors[i] = quantize_error(flatten_array[i])
223
       mse = np.mean(quantized_errors**2)
224
       return mse, F
  # Define the quantization function for prediction errors
228
  def quantize_error(error):
       if error < -1:</pre>
229
           return -1
230
       elif error >= -1 and error <= 1:
231
           return 0
232
233
       else:
234
           return 1
  # Define the optimization objective (minimize quantized MSE)
  def objective(weights):
238
       return calculate_mse_and_quantize_neighbors(weights, image_matrix)[0] #
           Use image_matrix instead of predefined matrix f
239
  \# Initial guess for weights (w_above, w_below, w_left, w_right)
240
  initial_weights = [0.25, 0.25, 0.25, 0.25]
241
242
   \# Add x1 + x2 + x3 + x4 = 1 as an equality constraint
243
  constraints = ({'type': 'eq', 'fun': lambda weights: weights[0] + weights[1] +
      weights[2] + weights[3] - 1},)
245
  # Define bounds for weights
246
  bounds = [(0, 1), (0, 1), (0, 1), (0, 1)] # weights between 0 and 1
247
248
  # Optimize weights to minimize quantized MSE
249
  result = minimize(objective, initial_weights, bounds=bounds,
250
      constraints=constraints)
251
  # Extract the optimized weights
  optimized_weights = result.x
  w_above_opt, w_below_opt, w_left_opt, w_right_opt = optimized_weights
  \# Print the optimized weights and quantized MSE
  print("Optimized Weights (w_above, w_below, w_left, w_right):",
      optimized_weights)
  print("Optimized Quantized MSE:", result.fun)
258
259
   # Calculating the predicted image using the optimized weights
260
  optimal_mse, predicted_matrix1 =
261
      calculate_mse_and_quantize_neighbors(optimized_weights, image_matrix)
  predicted_image1 = Image.fromarray(predicted_matrix1)
263
264
  # Display both the original and predicted images side by side
265
plt.figure(figsize=(12, 6))
267
268 # Original Image
269 plt.subplot(1, 2, 1)
plt.imshow(image_matrix, cmap='gray')
271 plt.title("Original Image")
272
273 # Predicted Image
274 plt.subplot(1, 2, 2)
plt.imshow(predicted_image1, cmap='gray')
276 plt.title("Predicted Image")
```

277

plt.show()

Results

We report the optimized weights and the quantized MSE for each approach, demonstrating the effectiveness of the optimization process in minimizing prediction errors. Finally, both the original and predicted images are displayed side by side for visual comparison.

In summary, our code showcases two distinct approaches for pixel value prediction in an image, each with its own consideration of neighboring pixels. The optimization process determines optimal weights to minimize the quantized MSE between the original and predicted images, resulting in varying levels of prediction accuracy for the two approaches.

Question 2

Take a black & white typeset document, encode the document using Runlength encoding and than G3 fax encoder, compare the results.

Solution

Python Code

```
import cv2
  from PIL import Image
  import numpy as np
  # Load the input image
  input_image = Image.open('doc.jpg')
  # Convert the input image to binary (black and white)
  binary_image = input_image.convert('1')
  # Save the binary image
  binary_image.save('result.jpg')
  # Get the size of the binary image
14
  image_size = binary_image.size
15
  # Function to perform run-length encoding on a binary image
17
  def rle_encode(image_array):
      shape = image_array.shape
      image_array = image_array.flatten()
20
21
      if len(image_array) == 0:
22
          return "0 0"
23
24
      encoded_data = f"{shape[0]} {shape[1]} "
25
      current_pixel = image_array[0]
      current_length = 1
      for i in range(1, len(image_array)):
30
          if image_array[i] != current_pixel:
               if current_pixel == True:
31
                   encoded_data += f"{1} {current_length} "
32
               else:
33
                   encoded_data += f"{0} {current_length} "
34
               current_pixel = image_array[i]
35
               current_length = 1
36
          else:
37
               current_length += 1
39
      if current_pixel == True:
40
          encoded_data += f"{1} {current_length}"
41
42
          encoded_data += f"{0} {current_length}"
43
      return encoded_data
44
45
  # Function to decode a run-length encoded string back to an image
46
  def rle_decode(encoded_data):
      arr = [int(x) for x in encoded_data.split()]
      rows = arr[0]
      cols = arr[1]
      data = arr[2:]
      decoded_data = []
```

```
54
       for i in range(0, len(data), 2):
55
           pixel_value = data[i]
56
           run_length = data[i + 1]
57
           decoded_data.extend([pixel_value] * run_length)
58
       decoded_data = np.array(decoded_data, dtype=np.uint8)
61
       decoded_image = Image.fromarray(decoded_data.reshape(rows, cols))
62
       return decoded_image
63
  # Function to encode the binary image using run-length encoding
64
  def rle_encode_image(binary_image):
65
       image_array = np.array(binary_image)
66
       encoded_image_data = rle_encode(image_array)
67
       return encoded_image_data
68
  # Load the input image
input_image = Image.open('doc.jpg')
72
73
  # Convert the input image to binary (black and white)
74 binary_image = input_image.convert('1')
  # Encode the binary image using run-length encoding
76
  rle_encoded_data = rle_encode_image(binary_image)
77
  # print('RLE encoded image data:', rle_encoded_data)
78
  # Save the encoded data to a text file
80
  with open("encoded_data.txt", "w") as encoded_file:
       encoded_file.write(rle_encoded_data)
  # Class to perform G3Fax encoding on a binary image
  class G3FaxEncoder:
87
       def __init__(self, image):
           self.image = image
88
           self.width = image.width
89
           self.height = image.height
       # Encode the binary image using G3Fax encoding
       def encode(self):
93
           bitstream = bytearray()
95
           # Start of page (SOP) marker
96
           bitstream.extend([0xFF, 0x00])
97
98
99
           image_data = list(self.image.getdata())
100
           for y in range(self.height):
               line = image_data[y * self.width: (y + 1) * self.width]
               run_length = 0
103
104
               for pixel in line:
105
                   if pixel == 0: # Black pixel
106
                       run_length += 1
107
                    else: # White pixel
108
                        if run_length > 0:
109
                            bitstream.extend(self.encode_run_length(run_length))
110
111
                        run_length = 0
112
               # End of line (EOL) marker
               bitstream.extend([0x00, 0x00])
114
115
           bitstream.extend([0x01, 0x00])
116
```

```
117
           return bitstream
118
       # Encode run length for G3Fax
119
       def encode_run_length(self, run_length):
120
           encoded = []
121
122
           while run_length >= 0x80:
                encoded.append(0x80 | (run_length & 0x7F))
                run_length >>= 7
126
           encoded.append(run_length)
           return encoded
127
128
   # Create an instance of the G3FaxEncoder
129
  g3fax_encoder = G3FaxEncoder(binary_image)
130
131
132
   # Encode the image using G3Fax and save it to a binary file
  g3fax_bitstream = g3fax_encoder.encode()
  with open('g3fax_bitstream.bin', 'wb') as f:
136
       f.write(g3fax_bitstream)
```

In the course of our analysis, we have examined two distinct compression methods, namely Run-Length Encoding (RLE) and G3 Fax Encoding. These methods were applied to an original image with a file size of 414KB to evaluate their respective compression efficiencies.

The results of our assessment are as follows:

- 1. Run-Length Encoding (RLE):
 - The RLE-encoded data produced an output size of 320KB.
 - Compression Ratio: 414KB/320KB = 1.29
- 2. G3 Fax Encoding:
 - The G3 Fax-encoded data yielded an output size of 44KB.
 - Compression Ratio: 414KB/44KB = 9.41

As higher the compression ratio, the smaller the file. So from the above observations, it becomes evident that the RLE method achieved a relatively lower compression ratio. This outcome is primarily attributed to the nature of RLE, which is effective for eliminating consecutive duplicate pixels but may not perform optimally for complex images.

In contrast, the G3 Fax Encoding method demonstrated significantly superior compression capabilities with a compression ratio. This remarkable result is a testament to the efficiency of G3 Fax Encoding in handling bi-level (black and white) images, particularly in scenarios such as scanned text documents.

In conclusion, while Run-Length Encoding (RLE) offers simplicity and ease of encoding and decoding, it falls short of achieving substantial compression for certain types of images. On the other hand, G3 Fax Encoding, although more complex to implement, excels in compression, making it a preferred choice for scenarios where efficient data compression is crucial.

Question 3

Compress the image used in Question 2 using

- a) Huffman coding
- b) DCT coding
- c) KL transform based coding
- d) use Haar wavelet and compress it

Compare the results in terms of compression

Solution

Python Code

```
import cv2
  import numpy as np
  from scipy.fftpack import dct, idct
  import matplotlib.pyplot as plt
  import pywt
  import huffman
  original_image = cv2.imread('doc3.jpg', cv2.IMREAD_GRAYSCALE)
  dct_image = dct(dct(original_image.T, norm='ortho').T, norm='ortho')
quantization_factor = 0.001
  quantized_dct_image = np.round(dct_image / quantization_factor)
| encoded_data = quantized_dct_image.flatten().astype(np.int16)
16 encoded_data.tofile('encoded_image.bin')
17
  decoded_dct_image = idct(idct(quantized_dct_image.T, norm='ortho').T,
     norm='ortho').astype(np.uint8)
20 # Display the original and decoded images
21 plt.subplot(1, 3, 1)
plt.imshow(original_image, cmap='gray')
plt.title('Original Image')
25 plt.subplot(1, 3, 2)
plt.imshow(quantized_dct_image, cmap='gray')
  plt.title('Encoded Image')
29 plt.subplot(1, 3, 3)
good plt.imshow(decoded_dct_image, cmap='gray')
  plt.title('Decoded Image')
33 plt.show()
36 # Load an image using OpenCV
original_image = cv2.imread('doc3.jpg', cv2.IMREAD_GRAYSCALE)
39 # Perform Haar wavelet transform
40 coeffs = pywt.dwt2(original_image, 'haar')
_{
m 42}| # Get the approximation and details coefficients
  cA, (cH, cV, cD) = coeffs
```

```
45 \# Display the coefficients or perform further processing as needed
  cv2.imshow('Approximation (cA)', cA)
46
  cv2.imshow('Horizontal Detail (cH)', cH)
47
  cv2.imshow('Vertical Detail (cV)', cV)
  cv2.imshow('Diagonal Detail (cD)', cD)
  cv2.waitKey(0)
52
  cv2.destroyAllWindows()
  # Load the image using OpenCV
55
  original_image = cv2.imread('doc3.jpg', cv2.IMREAD_GRAYSCALE)
56
  # Calculate pixel frequencies
58
59 pixel_frequencies = {}
  for row in original_image:
      for pixel_value in row:
          if pixel_value in pixel_frequencies:
63
              pixel_frequencies[pixel_value] += 1
64
              pixel_frequencies[pixel_value] = 1
65
66
  # Build the Huffman tree
67
  huff_tree = huffman.build_tree(pixel_frequencies)
68
70
  # Generate Huffman codes
  huff_codes = huffman.get_codes(huff_tree)
73
  # Encode the image using Huffman codes
  encoded_image = []
  for row in original_image:
75
      encoded_row = [huff_codes[pixel] for pixel in row]
77
      encoded_image.append(encoded_row)
  with open('encoded_image.txt', 'w') as f:
79
      for row in encoded_image:
80
          f.write(''.join(row) + '\n')
```

KL Transform based coding MATLAB Code

```
1 clc;
2 close all;
3 clear all;
4 I=imread('cameraman.tif');
5 I=im2double(I);
_{6} m=1;
  for i=1:8:256
       for j=1:8:256
           for x=0:7
                for y=0:7
10
                     img(x+1,y+1)=I(i+x,j+y);
11
                end
12
13
           end
14
           k=0;
15
           for 1=1:8
16
                img_expect{k+1}=img(:,1)*img(:,1)';
17
                k=k+1;
18
19
20
           imgexp=zeros(8:8);
           for 1=1:8
```

```
imgexp=imgexp+(1/8)*img_expect{1};
23
                % expectation of E[xx']
24
           end
25
26
           img_mean=zeros(8,1);
27
           for 1=1:8
28
29
                img_mean = img_mean + (1/8) * img(:,1);
30
           end
31
           img_mean_trans=img_mean*img_mean';
32
           img_covariance=imgexp - img_mean_trans;
33
           [v{m},d{m}] = eig(img_covariance);
34
           temp=v{m};
35
           m = m + 1;
36
37
           for l=1:8
38
                v\{m-1\}(:,1) = temp(:,8-(1-1));
40
           end
41
42
           for 1=1:8
                trans_img1(:,1)=v\{m-1\}*img(:,1);
43
44
           end
45
           for x=0:7
46
                for y=0:7
47
48
                     transformed_img(i+x,j+y)=trans_img1(x+1,y+1);
49
                end
50
           end
51
           mask = [1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1 \ 1
52
                  1 1 1 1 1 1 1 1
53
                  1 1 1 1 1 1 1 1
54
                  1 1 1 1 1 1 1 1
55
                  1 1 1 1 1 1 1 1
56
                  1 1 1 1 1 1 1 1
57
                  1 1 1 1 1 1 1 1
58
59
                  1 1 1 1 1 1 1 1 ];
           trans_img=trans_img1.*mask;
           for 1=1:8
                inv_trans_img(:,1)=v{m-1}'*trans_img(:,1);
63
           end
64
65
           for x=0:7
66
                for y=0:7
67
68
                     inv_transformed_img(i+x,j+y)=inv_trans_img(x+1,y+1);
                end
69
70
           end
71
72
       end
  end
73
  imshow(transformed_img);
74
75
  figure
76
imshow(inv_transformed_img);
```

```
from PIL import Image
import numpy as np
image path = '/content/harry.jpg'
image = Image.open(image path)
# Converting the image to grayscale
if image.mode != 'L':
    image = image.convert('L')
# Converting the grayscale image to a NumPy matrix
image matrix = np.array(image)
print("Image Matrix Shape:", image matrix.shape)
Image Matrix Shape: (400, 400)
import numpy as np
from scipy.optimize import minimize
import matplotlib.pyplot as plt
f = image matrix
# Define the objective function to calculate MSE and then quantize
error
def calculate mse and quantize(weights, original image):
    w1, w2 = weights
    M, N = original image.shape
    F = np.zeros((M, N))
    for i in range(M):
        for j in range(N):
            if i == 0 and i == 0:
                F[i][j] = (<mark>int</mark>)(original image[i][j])
            elif i == 0:
                \# F[i][j] = w1*F[i][j-1]
                F[i][j] = (int)(original image[i][j])
            elif j == 0:
                \# F[i][i] = w2*F[i-1][i]
                F[i][j] = (int)(original image[i][j])
            else:
                F[i][j] = (int)(w1 * original image[i][j-1] + w2 *
original image[i-1][j])
    prediction errors = original image - F
    flatten array = prediction errors.flatten()
    quantized errors = np.zeros(flatten array.size)
    # print(flatten_array.size)
    for i in range(flatten array.size):
      quantized errors[i] = quantize error(flatten array[i])
```

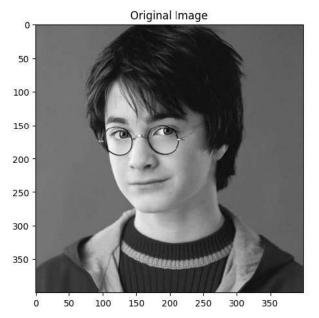
```
mse = np.mean(quantized errors**2)
    return mse, F
# Define the quantization function for prediction errors
def quantize error(error):
    if error < -1:
        return -1
    elif error >= -1 and error <= 1:
        return 0
    else:
        return 1
# Define the optimization objective (minimize quantized MSE)
def objective(weights):
    return calculate mse and quantize(weights, image matrix)[0] # Use
image matrix instead of predefined matrix f
# Initial guess for weights (w1, w2)
initial weights = [0.5, 0.5]
# Define bounds for weights
bounds = [(0, 1), (0, 1)]
\# Add x1 + x2 = 1 as an equality constraint
constraints = ({'type': 'eq', 'fun': lambda weights: weights[0] +
weights[1] - 1},)
# Optimize weights to minimize quantized MSE
result = minimize(objective, initial weights, bounds=bounds,
constraints=constraints)
# Extracting the optimized weights
optimized weights = result.x
w1 optimized, w2 optimized = optimized weights
# Print the optimized weights and quantized MSE
print("Optimized Weights (w1, w2):", optimized weights)
print("Optimized Quantized MSE:", result.fun)
# Calculating the predicted image using the optimized weights
optimal mse, predicted matrix =
calculate mse and quantize(optimized weights, image matrix)
predicted image = Image.fromarray(predicted matrix)
# Display both the original and predicted images side by side
plt.figure(figsize=(12, 6))
# Original Image
```

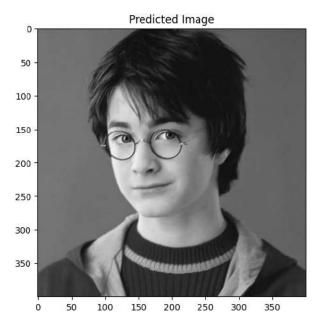
```
plt.subplot(1, 2, 1)
plt.imshow(image_matrix, cmap='gray')
plt.title("Original Image")

# Predicted Image
plt.subplot(1, 2, 2)
plt.imshow(predicted_image, cmap='gray')
plt.title("Predicted Image")

plt.show()

Optimized Weights (w1, w2): [0.5 0.5]
Optimized Quantized MSE: 0.346225
```





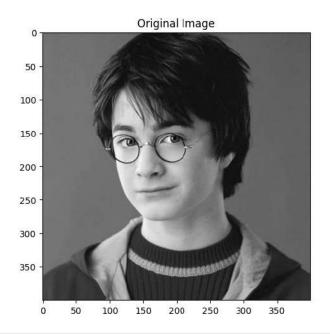
```
# In the below code we tried to experiment it using the updated values
to predict the new pixel values

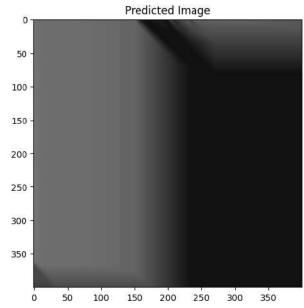
# Define the objective function to calculate MSE and then quantize
error
def calculate_mse_and_quantize(weights, original_image):
    w1, w2 = weights
    M, N = original_image.shape
    F = np.zeros((M, N))

for i in range(N):
    if i == 0 and j == 0:
        F[i][j] = (int)(original_image[i][j])
    elif i == 0:
        # F[i][j] = w1*F[i][j-1]
```

```
F[i][j] = (int)(original image[i][j])
            elif j == 0:
                \# F[i][j] = w2*F[i-1][j]
                F[i][j] = (int)(original image[i][j])
            else:
                F[i][j] = (int)(w1 * F[i][j-1] + w2 * F[i-1][j])
    prediction errors = original image - F
    flatten array = prediction errors.flatten()
    quantized errors = np.zeros(flatten_array.size)
    # print(flatten array.size)
    for i in range(flatten array.size):
      quantized errors[i] = quantize error(flatten array[i])
    mse = np.mean(quantized errors**2)
    return mse, F
# Define the quantization function for prediction errors
def quantize error(error):
    if error < -1:
        return -1
    elif error >= -1 and error <= 1:
        return 0
    else:
        return 1
# Define the optimization objective
def objective(weights):
    return calculate_mse_and_quantize(weights, image matrix)[0] # Use
image matrix instead of predefined matrix f
# Initial guess for weights (w1, w2)
initial weights = [0.5, 0.5]
# Define bounds for weights
bounds = [(0, 1), (0, 1)] # weights between 0 and 1
\# Add x1 + x2 = 1 as an equality constraint
constraints = ({'type': 'eq', 'fun': lambda weights: weights[0] +
weights[1] - 1},)
# Optimize weights to minimize quantized MSE
result = minimize(objective, initial weights, bounds=bounds,
constraints=constraints)
# Extract the optimized weights
optimized weights = result.x
w1 optimized, w2 optimized = optimized weights
# print("optimized weights:", result.x)
```

```
# Print the optimized weights and quantized MSE
print("Optimized Weights (w1, w2):", optimized weights)
print("Optimized Quantized MSE:", result.fun)
# Calculating the predicted image using the optimized weights
optimal mse, predicted matrix =
calculate_mse_and_quantize(optimized_weights, image_matrix)
predicted image = Image.fromarray(predicted matrix)
# Display both the original and predicted images side by side
plt.figure(figsize=(12, 6))
# Original Image
plt.subplot(1, 2, 1)
plt.imshow(image matrix, cmap='gray')
plt.title("Original Image")
# Predicted Image
plt.subplot(1, 2, 2)
plt.imshow(predicted image, cmap='gray')
plt.title("Predicted Image")
plt.show()
Optimized Weights (w1, w2): [0.5 0.5]
Optimized Quantized MSE: 0.9601125
```

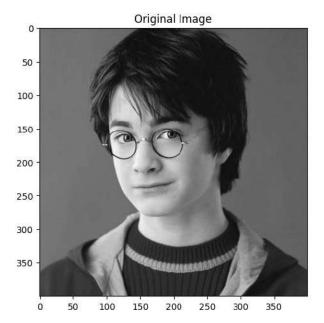


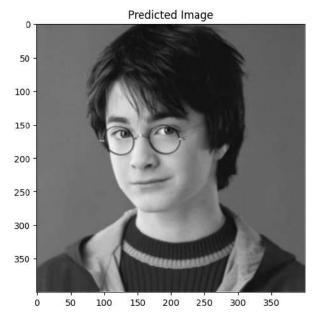


4 neighbours to predict the pixel value
def calculate_mse_and_quantize_neighbors(weights, original_image):

```
w above, w below, w left, w right = weights
    M, N = original image.shape
    F = np.zeros((M, N))
    for i in range(M):
        for j in range(N):
            if i == 0 and j == 0:
                F[i][j] = original image[i][j]
            elif i == 0:
                \# F[i][j] = (w \text{ left } * F[i][j-1] + \text{ original image}[i]
[j]) / (w_left + 1)
                F[i][j] = original image[i][j]
            elif j == 0:
                \# F[i][j] = (w \ above \ * F[i - 1][j] + original \ image[i]
[j]) / (w above + 1)
                F[i][j] = original image[i][j]
            else:
                neighbors = [
                    w above * original image[i - 1][j],
                                                              # Above
                    w below * original image[i + 1][j] if i + 1 < M
else original image[i][j], # Below (with boundary check)
                    w left * original_image[i][j - 1],
                    w right * original image[i][j + 1] if j + 1 < N
else original_image[i][j] # Right (with boundary check)
                F[i][j] = sum(neighbors)
    prediction errors = original image - F
    flatten array = prediction errors.flatten()
    quantized errors = np.zeros(flatten array.size)
    # print(flatten array.size)
    for i in range(flatten array.size):
      quantized errors[i] = quantize error(flatten array[i])
    mse = np.mean(quantized errors**2)
    return mse, F
# Define the quantization function for prediction errors
def quantize error(error):
    if error < -1:
        return -1
    elif error >= -1 and error <= 1:
        return 0
    else:
        return 1
# Define the optimization objective (minimize quantized MSE)
def objective(weights):
    return calculate_mse_and_quantize_neighbors(weights, image_matrix)
[0] # Use image matrix instead of predefined matrix f
```

```
# Initial guess for weights (w above, w below, w left, w right)
initial weights = [0.25, 0.25, 0.25, 0.25]
\# Add x1 + x2 + x3 + x4 = 1 as an equality constraint
constraints = ({'type': 'eq', 'fun': lambda weights: weights[0] +
weights[1] + weights[2] + weights[3] - 1,)
# Define bounds for weights
bounds = [(0, 1), (0, 1), (0, 1), (0, 1)] # weights between 0 and 1
# Optimize weights to minimize quantized MSE
result = minimize(objective, initial weights, bounds=bounds,
constraints=constraints)
# Extract the optimized weights
optimized weights = result.x
w above opt, w below opt, w left opt, w right opt = optimized weights
# Print the optimized weights and quantized MSE
print("Optimized Weights (w above, w below, w left, w right):",
optimized weights)
print("Optimized Quantized MSE:", result.fun)
# Calculating the predicted image using the optimized weights
optimal mse, predicted matrix1 =
calculate mse and quantize neighbors(optimized weights, image matrix)
predicted image1 = Image.fromarray(predicted matrix1)
# Display both the original and predicted images side by side
plt.figure(figsize=(12, 6))
# Original Image
plt.subplot(1, 2, 1)
plt.imshow(image matrix, cmap='gray')
plt.title("Original Image")
# Predicted Image
plt.subplot(1, 2, 2)
plt.imshow(predicted image1, cmap='gray')
plt.title("Predicted Image")
plt.show()
Optimized Weights (w above, w below, w left, w right): [0.25 0.25 0.25
Optimized Quantized MSE: 0.30706875
```





q2-a4

October 8, 2023

```
[5]: import cv2
      from PIL import Image
      import numpy as np
      from google.colab.patches import cv2_imshow
 [6]: | image = Image.open('doc.jpg')
      image_binary = image.convert('1')
      image_binary.save('result.jpg')
      image_binary.size
 [6]: (2481, 3508)
[18]: from pickle import STRING
      import collections
      from PIL import Image
      import numpy as np
      def rle_encode(image_array):
        shape = image_array.shape
        image_array = image_array.flatten() # flatteing the array to get 1-D array
        if len(image_array) == 0: return "0 0"
        enc = f"{shape[0]} {shape[1]} "
        cur_char = image_array[0]
        cur_len = 1
        for i in range(1, len(image_array)):
          if image_array[i]!=cur_char:
            if cur_char==True:
              enc+= f"{1} {cur_len} "
              enc+= f"{0} {cur_len} "
            cur_char = image_array[i]
            cur_len = 1
          else:
            cur len+=1
        if cur_char==True:
          enc+= f"{1} {cur len}"
        else:
```

```
enc+= f"{0} {cur_len}"
  return enc
def rle_decode(string):
  arr = [int(x) for x in string.split()]
  row = arr[0]
  col = arr[1]
 res = []
  arr = arr[2:]
 for i in range(0, len(arr),2):
   res.extend([arr[i]]*arr[i+1])
 res = np.array(res)
  print("="*10,len(res), row, col, row*col)
  res.reshape((row, col))
  decoded_image = Image.fromarray(res)
  return decoded_image
def rle_encode_image(image):
  # Convert the image to a NumPy array.
  image_array = np.array(image_binary)
  # Encode the flattened image array using RLE.
  encoded_image_data = rle_encode(image_array)
  # Return the encoded image data.
 return encoded_image_data
image = Image.open('doc.jpg')
rle_encoded_image_data = rle_encode_image(image)
print('RLE encoded image data:', rle_encoded_image_data)
file = open("encode.txt", "w")
file.write(rle_encoded_image_data) # storing the encoding in the form of __
 \hookrightarrowstring to a .txt file
file.close()
```

RLE encoded image data: 3508 2481 1 790121 0 1 1 1 0 1 1 2407 0 5 1 65 0 5 1 215 0 9 1 2181 0 7 1 64 0 6 1 212 0 14 1 2178 0 7 1 64 0 5 1 211 0 17 1 2177 0 8 1 63 0 6 1 173 0 3 1 33 0 18 1 2176 0 9 1 63 0 5 1 173 0 5 1 32 0 6 1 5 0 8 1 2175 0 4 1 1 0 5 1 241 0 4 1 32 0 4 1 9 0 7 1 2174 0 4 1 1 0 5 1 240 0 5 1 32 0 2 1 12 0 6 1 2173 0 5 1 1 0 5 1 241 0 4 1 46 0 6 1 2173 0 4 1 3 0 5 1 239 0 5 1 47 0 6 1 2171 0 5 1 3 0 5 1 22 0 1 1 22 0 1 1 36 0 1 1 31 0 1 1 29 0 1 1 15 0 1 1 27

6 1 13 0 4 1 24 0 4 1 7 0 4 1 7 0 6 1 9 0 4 1 8 0 4 1 11 0 4 1 6 0 5 1 9 0 5 1 2248 0 4 1 11 0 4 1 7 0 4 1 10 0 5 1 8 0 4 1 11 0 4 1 11 0 4 1 7 0 5 1 13 0 3 1 25 0 4 1 8 0 4 1 7 0 4 1 10 0 5 1 7 0 4 1 11 0 4 1 6 0 4 1 11 0 5 1 2247 0 3 1 12 0 4 1 7 0 4 1 11 0 3 1 10 0 4 1 10 0 4 1 11 0 4 1 7 0 4 1 13 0 5 1 24 0 4 1 8 0 4 1 7 0 4 1 11 0 3 1 8 0 4 1 11 0 4 1 6 0 4 1 12 0 3 1 2247 0 5 1 11 0 4 1 7 0 4 1 10 0 5 1 9 0 4 1 9 0 4 1 12 0 4 1 7 0 4 1 14 0 4 1 24 0 4 1 8 0 4 1 7 0 4 1 10 0 5 1 6 0 4 1 13 0 3 1 5 0 5 1 11 0 5 1 2246 0 21 1 5 0 4 1 12 0 4 1 8 0 5 1 9 0 16 1 1 0 4 1 5 0 5 1 14 0 4 1 18 0 1 1 1 0 2 1 1 0 1 1 1 0 3 1 7 0 5 1 7 0 4 1 11 0 4 1 6 0 21 1 4 0 4 1 13 0 3 1 2247 0 20 1 7 0 4 1 11 0 4 1 9 0 4 1 9 0 20 1 7 0 4 1 14 0 4 1 14 0 14 1 8 0 4 1 6 0 4 1 12 0 4 1 6 0 20 1 5 0 5 1 11 0 5 1 2246 0 20 1 7 0 4 1 11 0 4 1 9 0 4 1 9 0 20 1 7 0 4 1 14 0 4 1 13 0 15 1 8 0 3 1 8 0 4 1 10 0 5 1 6 0 20 1 5 0 4 1 13 0 3 1 2248 0 3 1 23 0 4 1 10 0 5 1 8 0 4 1 10 0 4 1 23 0 3 1 14 0 4 1 13 0 6 1 1 0 1 1 4 0 4 1 8 0 4 1 7 0 4 1 11 0 3 1 7 0 4 1 21 0 4 1 12 0 5 1 2246 0 5 1 21 0 5 1 11 0 3 1 10 0 4 1 9 0 5 1 21 0 5 1 14 0 4 1 11 0 5 1 8 0 5 1 6 0 5 1 7 0 4 1 11 0 4 1 6 0 5 1 21 0 4 1 11 0 4 1 2247 0 4 1 23 0 4 1 11 0 4 1 9 0 4 1 10 0 3 1 23 0 4 1 14 0 4 1 10 0 5 1 9 0 4 1 8 0 4 1 7 0 4 1 11 0 4 1 7 0 3 1 21 0 5 1 12 0 4 1 2247 0 4 1 22 0 3 1 12 0 4 1 9 0 4 1 9 0 5 1 22 0 4 1 14 0 4 1 10 0 4 1 10 0 4 1 8 0 4 1 6 0 5 1 11 0 4 1 6 0 5 1 21 0 4 1 11 0 4 1 2248 0 4 1 22 0 4 1 11 0 4 1 8 0 5 1 10 0 4 1 21 0 5 1 14 0 4 1 10 0 4 1 10 0 4 1 8 0 4 1 7 0 3 1 11 0 5 1 7 0 4 1 21 0 4 1 11 0 5 1 2247 0 5 1 20 0 5 1 10 0 5 1 9 0 4 1 10 0 5 1 21 0 3 1 14 0 5 1 10 0 5 1 9 0 4 1 7 0 4 1 8 0 4 1 11 0 3 1 8 0 5 1 20 0 5 1 9 0 5 1 10 0 1 1 2238 0 4 1 12 0 1 1 8 0 4 1 11 0 4 1 9 0 4 1 11 0 4 1 12 0 1 1 8 0 4 1 14 0 4 1 11 0 3 1 9 0 5 1 8 0 4 1 7 0 4 1 11 0 4 1 8 0 4 1 12 0 1 1 7 0 5 1 8 0 7 1 7 0 5 1 2236 0 6 1 7 0 5 1 7 0 4 1 11 0 3 1 10 0 5 1 4 0 1 1 5 0 6 1 7 0 5 1 6 0 5 1 14 0 5 1 4 0 1 1 4 0 6 1 5 0 7 1 8 0 4 1 6 0 5 1 11 0 4 1 8 0 6 1 7 0 5 1 7 0 6 1 4 0 8 1 8 0 5 1 2237 0 16 1 8 0 4 1 11 0 4 1 9 0 10 1 6 0 16 1 8 0 4 1 14 0 10 1 5 0 17 1 8 0 4 1 7 0 4 1 10 0 5 1 9 0 16 1 9 0 13 1 1 0 4 1 7 0 5 1 2238 0 15 1 7 0 5 1 11 0 4 1 10 0 9 1 7 0 15 1 8 0 4 1 15 0 9 1 6 0 11 1 2 0 3 1 7 0 5 1 7 0 3 1 12 0 3 1 11 0 15 1 10 0 11 1 2 0 3 1 8 0 5 1 2240 0 10 1 1 0 1 1 9 0 3 1 11 0 4 1 13 0 7 1 9 0 10 1 1 0 1 1 8 0 4 1 18 0 7 1 8 0 7 1 4 0 3 1 8 0 3 1 8 0 4 1 11 0 4 1 12 0 11 1 13 0 8 1 4 0 4 1 7 0 4 1 2244 0 1 1 1 0 1 1 1 0 1 1 46 0 1 1 16 0 1 1 1 0 1 1 38 0 1 1 14 0 1 1 12 0 1 1 51 0 1 1 1 0 1 1 21 0 1 1 1 0 1 1 3527305

```
[19]: import numpy as np
from PIL import Image

class G3FaxEncoder:

def __init__(self, image):

    self.image = image
    self.width = image.width
    self.height = image.height

def encode(self):
```

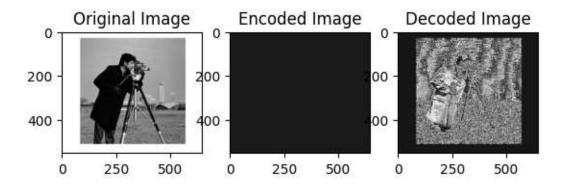
```
# Initialize the bitstream
      bitstream = bytearray()
      # Start of page (SOP) marker
      bitstream.extend([0xFF, 0x00])
      # Convert image data to a list
      image_data = list(self.image.getdata())
      # Iterate over image lines
      for y in range(self.height):
          line = image_data[y * self.width: (y + 1) * self.width]
          # Run-length encoding (RLE) for black and white pixels
          run_length = 0
          for pixel in line:
              if pixel == 0: # Black pixel
                  run_length += 1
              else: # White pixel
                  if run_length > 0:
                      bitstream.extend(self.encode_run_length(run_length))
                  run_length = 0
          # End of line (EOL) marker
          bitstream.extend([0x00, 0x00])
     bitstream.extend([0x01, 0x00])
     return bitstream
   def encode_run_length(self, run_length):
        encoded = []
        while run_length >= 0x80:
            encoded.append(0x80 | (run_length & 0x7F))
            run_length >>= 7
        encoded.append(run_length)
       return encoded
image = Image.open('doc.jpg').convert('1') # converting it to a black and white_
⇒image
# Create the G3FaxEncoder instance
encoder = G3FaxEncoder(image)
```

```
# Encode the image and save it to a file
bitstream = encoder.encode()
with open('bitstream.bin', 'wb') as f: # outputting it to a .bin file
    f.write(bitstream)
```

ell715q3

October 10, 2023

```
[5]: import cv2
     import numpy as np
     from scipy.fftpack import dct, idct
     import matplotlib.pyplot as plt
     import pywt
     import huffman
[3]: original_image = cv2.imread('doc3.jpg', cv2.IMREAD_GRAYSCALE)
     dct_image = dct(dct(original_image.T, norm='ortho').T, norm='ortho')
     quantization factor = 0.001
     quantized_dct_image = np.round(dct_image / quantization_factor)
     encoded_data = quantized_dct_image.flatten().astype(np.int16)
     encoded_data.tofile('encoded_image.bin')
     decoded_dct_image = idct(idct(quantized_dct_image.T, norm='ortho').T,__
      →norm='ortho').astype(np.uint8)
     # Display the original and decoded images
     plt.subplot(1, 3, 1)
     plt.imshow(original_image, cmap='gray')
     plt.title('Original Image')
     plt.subplot(1, 3, 2)
     plt.imshow(quantized_dct_image, cmap='gray')
     plt.title('Encoded Image')
     plt.subplot(1, 3, 3)
     plt.imshow(decoded_dct_image, cmap='gray')
     plt.title('Decoded Image')
     plt.show()
```



```
[6]: # Load an image using OpenCV
    original_image = cv2.imread('doc3.jpg', cv2.IMREAD_GRAYSCALE)

# Perform Haar wavelet transform
    coeffs = pywt.dwt2(original_image, 'haar')

# Get the approximation and details coefficients
    cA, (cH, cV, cD) = coeffs

# Display the coefficients or perform further processing as needed
    cv2.imshow('Approximation (cA)', cA)
    cv2.imshow('Horizontal Detail (cH)', cH)
    cv2.imshow('Vertical Detail (cV)', cV)
    cv2.imshow('Diagonal Detail (cD)', cD)

cv2.waitKey(0)
    cv2.destroyAllWindows()
```

```
huff_codes = huffman.get_codes(huff_tree)

# Encode the image using Huffman codes
encoded_image = []
for row in original_image:
    encoded_row = [huff_codes[pixel] for pixel in row]
    encoded_image.append(encoded_row)

with open('encoded_image.txt', 'w') as f:
    for row in encoded_image:
        f.write(' '.join(row) + '\n')
```

[]:

```
clc;
close all;
clear all;
I=imread('cameraman.tif');
I=im2double(I);
m=1;
for i=1:8:256
    for j=1:8:256
        for x=0:7
            for y=0:7
            img(x+1,y+1)=I(i+x,j+y);
            end
        end
            k=0;
            for l=1:8
                img_expect\{k+1\}=img(:,1)*img(:,1)';
                k=k+1;
            end
            imgexp=zeros(8:8);
            for 1=1:8
                imgexp=imgexp+(1/8)*img_expect{1};%expectation of E[xx']
            end
            img_mean=zeros(8,1);
            for 1=1:8
                img_mean=img_mean+(1/8)*img(:,1);
            end
            img_mean_trans=img_mean*img_mean';
            img_covariance=imgexp - img_mean_trans;
            [v{m},d{m}]=eig(img_covariance);
            temp=v{m};
             m=m+1;
            for 1=1:8
                v\{m-1\}(:,1)=temp(:,8-(1-1));
            end
             for 1=1:8
           trans_img1(:,1)=v\{m-1\}*img(:,1);
             end
           for x=0:7
               for y=0:7
                    transformed_img(i+x,j+y)=trans_img1(x+1,y+1);
               end
           end
mask=[1 1 1 1 1 1 1 1
      1 1 1 1 1 1 1 1
      1 1 1 1 1 1 1 1
      1 1 1 1 1 1 1 1
      1 1 1 1 1 1 1 1
      1 1 1 1 1 1 1 1
      1 1 1 1 1 1 1 1
      1 1 1 1 1 1 1 1 ];
```

```
trans_img=trans_img1.*mask;
    for l=1:8
    inv_trans_img(:,1)=v{m-1}'*trans_img(:,1);
    end
    for x=0:7
        for y=0:7
            inv_transformed_img(i+x,j+y)=inv_trans_img(x+1,y+1);
        end
    end
end
end
end
imshow(transformed_img);
```



```
figure
imshow(inv_transformed_img);
```

