ECE-6123 Nikita Makarov HW3

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- 0.0.1 ECE-GY 6123
- 0.0.2 Nikita Makarov, Fall 2024
- 0.0.3 Homework 3

Problem 1a:

```
[2]: import numpy as np
     import cv2
     %matplotlib inline
     from matplotlib import pyplot as plt
     # Create Gaussian Pyramid function
     def gaussian_pyramid(im_data: np.ndarray, J: int) -> list[np.ndarray]:
         Compute and return the J-level Gaussian pyramid decomposition of a_{\sqcup}
      ⇔grayscale image.
         Parameters:
         im_data: 2D numpy array of the image data in grayscale
         J: int of the Gaussian pyramid level
         Returns:
         G: list of size J filled with 2D numpy arrays of the Gaussian pyramid, with
      ⇔the first element being level 0
         111
         # Create Gaussian pyramid structure
         G = [im_data] # Create list with last element as level J
         # Iterate over all remaining levels
         for _ in range(0,J):
             width = int(im_data.shape[1]/2) # Calculate new width
             height = int(im_data.shape[0]/2) # Calculate new height
             im_data = cv2.resize(im_data,(width,height),interpolation=cv2.
      →INTER_LINEAR) # Get next layer of image data
             G.insert(0, im_data) # Add new layer to front of list
```

```
return G
# Create Laplacian Pyramid function
def laplacian pyramid(im_data: np.ndarray, J: int) -> list[np.ndarray]:
    Compute and return the J-level Laplacian pyramid decomposition of a_
 \hookrightarrow grayscale image.
    Parameters:
    im_data: 2D numpy array of the image data in grayscale
    J: int of the Laplacian pyramid level
   Returns:
    L: list of size J filled with 2D numpy arrays of the Laplacian pyramid, \Box
 \negwith the first element being level 0
    # Calculate Gaussian pyramid structure
    G = gaussian_pyramid(im_data, J)
    # Create Laplacian pyramid structure
    L = [G[0]] # Create list with first element as level 0
    # Iterate over all remaining levels
    for i in range(0,J):
        im_data = G[i+1] # Get first element in Gaussian pyramid
        (height, width) = im data.shape # Get new width and height
        U = cv2.resize(G[i],(width,height),interpolation=cv2.INTER_CUBIC) #_
 →Perform upscaling for next layer
        L.append(im_data - U) # Add new layer to end of list
    return L
```

Problem 1b:

```
# Create reconstructed image structure
    R = [L[0]]
    # Iterate over levels of the laplacian pyramid
    for i in range(0,len(L)-1):
        (height, width) = L[i+1].shape # Get new width and height
        U = cv2.resize(R[i],(width,height),interpolation=cv2.INTER_CUBIC) #_
 →Perform upscaling for next layer
        R.append(L[i+1] + U) # Calculate new reconstructed layer
    return R
# Create function for composite arrays for image display
def composite_image(P: list[np.ndarray]) -> np.ndarray:
    Create a composite array from a Gaussian or Laplacian pyramid structure.
    Parameters:
    P: list filled with 2D numpy arrays of the Gaussian or Laplacian pyramids,
 \negwith the first element being element 0
    Returns:
    C: 2D numpy array of the composite image
    111
    # If pyramid has one element, just return that level
    if len(P) == 1:
        return P[0]
    # Create initial composite array
    height = \max(np.shape(P[-1])[0], sum([np.shape(x)[0] for x in P[:-1]])) #_{U}
 → Total height of composite image
    width = np.shape(P[-1])[1] + np.shape(P[-2])[1] # Total width of composite_
 \hookrightarrow image
    C = np.full((height, width), np.nan) # Composite image array full of nan
    # Populate composite array
    height, width = np.shape(P[-1])
    C[:height, :width] = P[-1]
    height = 0
    P.reverse()
    for lvl in P[1:]:
        rows, cols = np.shape(lvl)
        C[height:height+rows, width:width+cols] = lvl
        height += rows
```

```
return C
# Test reconstruction with a sample image
image = np.asarray(cv2.imread('lighthouse.png', cv2.
→IMREAD_GRAYSCALE),dtype=float)
J = 3
G = gaussian_pyramid(image, J) # Gaussian pyramid
L = laplacian_pyramid(image, J) # Laplacian pyramid
R = reconstruct_laplacian(L) # Reconstructed image
# Create figure for original image
plt.figure()
plt.imshow(image, interpolation='none', cmap='gray')
plt.title('Original image')
plt.axis('off')
# Create figure for composite Gaussian image
C = composite_image(G)
plt.figure()
plt.imshow(C, interpolation='none', cmap='gray')
plt.title(f'Gaussian pyramid, J={J}')
plt.axis('off')
# Create figure for composite Laplacian image
C = composite_image(L)
plt.figure()
plt.imshow(C, interpolation='none', cmap='gray')
plt.title(f'Laplacian pyramidm J={J}')
plt.axis('off')
# Create figure for reconstructed image
C = composite_image(R)
plt.figure()
plt.imshow(C, interpolation='none', cmap='gray')
plt.title('Reconstructed image')
plt.axis('off')
```

[3]: (np.float64(-0.5), np.float64(1151.5), np.float64(511.5), np.float64(-0.5))

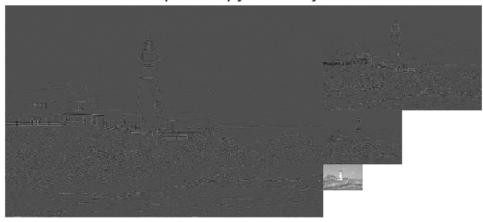
Original image



Gaussian pyramid, J=3



Laplacian pyramidm J=3



Reconstructed image



Problem 1c:

```
[4]: # Create function for quantize pyramid

def quantize_pyramid(P: list[np.ndarray], q: float, ep: float) → list[np.

ondarray]:

'''

Quantize the coefficients of the given pyramid with given step size and

ogiven mean.

Parameters:

P: list filled with 2D numpy arrays of the Gaussian or Laplacian pyramids,

with the first element being element 0

q: float of the quantization step size
```

```
ep: float of the mean of the coefficient map

Returns:
Q: list filled with 2D numpy arrays of the quantized pyramid, with the
first element being element 0

""

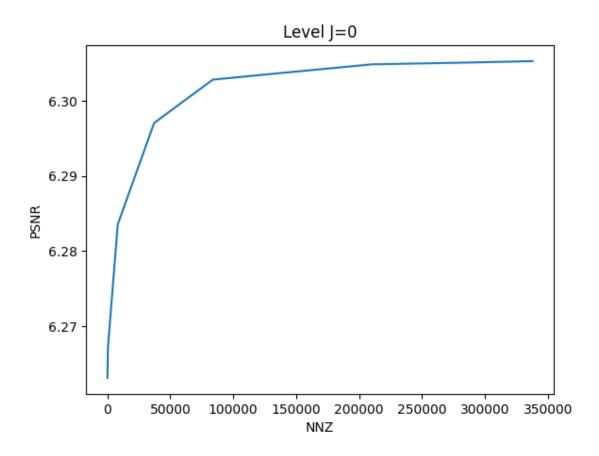
# Create initial quantized pyramid
Q = []

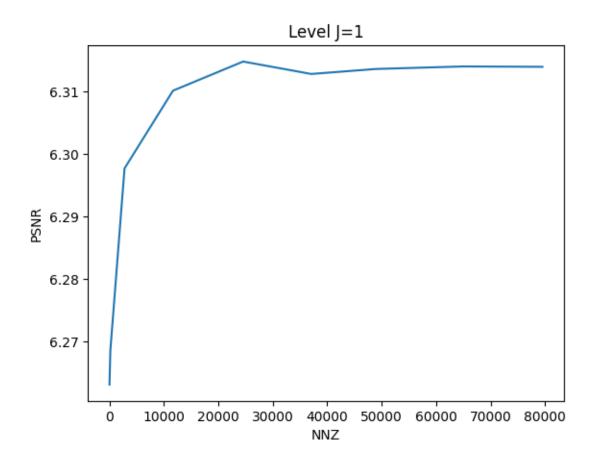
# Iterate over given pyramid and fill quantize pyramid
for lvl in P:
Q.append(q*np.floor((lvl-ep)/q + 1/2) + ep)

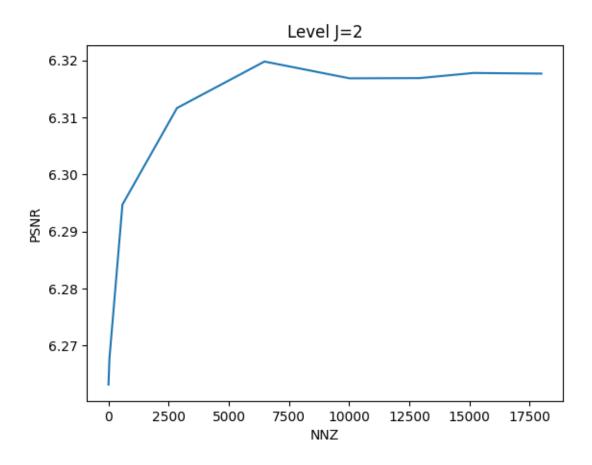
return Q
```

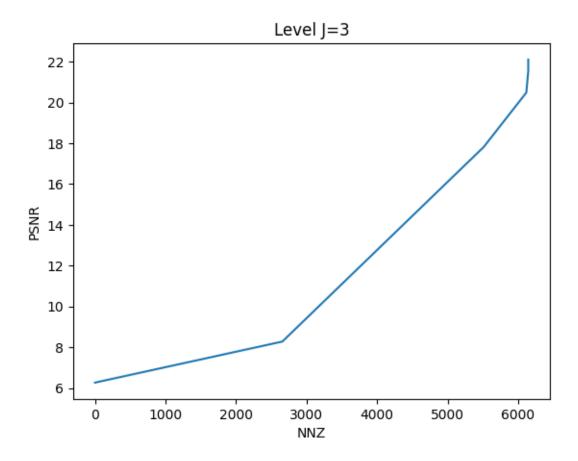
Problem 1d:

```
[5]: # Create initial PSNR and NNZ arrays
     q = 9
     PSNR = np.zeros((q+1,J+1))
     NNZ = np.zeros((q+1,J+1))
     [rows,cols] = np.shape(image)
     # Calculate quantized pyramids
     for n in range(q+1):
         Q = quantize_pyramid(L, 2**n, 0)
         R = reconstruct_laplacian(Q)
         # Calculate PSNR and NNZ for given levels
         for i in range(J+1):
             R_U = cv2.resize(R[i], (cols,rows))
             MSE = np.mean((image - R_U)**2) # Mean squared error
             PSNR[n,i] = 10*np.log10((255**2)/MSE) # Peak signal to noise ratio, for
      ⇒image in range [0,255]
             NNZ[n,i] = np.sum(Q[i] != 0)
     # Plot PSNR vs NNZ
     for i in range(J+1):
        plt.figure()
         plt.plot(NNZ[:,i], PSNR[:,i])
         plt.xlabel('NNZ')
         plt.ylabel('PSNR')
         plt.title(f'Level J={i}')
```









As the pyramid level increases, the image size gets smaller, since level 0 is the original image. At a certain point, specifically J=3, the PSNR for the given pyramid level increases at an exponential rate. This is somewhat expected, since as the pyramid level increases, we loose more and more of the data from the original image, so the potential error also increases.

Problem 1e:

For J=3, the curve shape of the PSNR vs NNZ plot has flipped. Instead of the PSNR reaching an equilibrium with the number of non-zero elements, it starts increasing exponentially. It appears that at around 6000 number of non-zeros the PSNR starts increasing faster than the NNZ.

Problem 2a:

```
Parameters:
    im_data: 2D numpy array of the image data in grayscale
    J: int of the levels
    Returns:
    coeffs: list of the approximation and coefficients for each level
    coeffs = []
    # Calculate coefficients
    for _ in range(J):
        (im_data, (cH, cV, cD)) = pywt.dwt2(im_data, 'haar')
        coeffs.insert(0, (cH, cV, cD))
    coeffs.insert(0, im_data)
    return coeffs
# Reconstruct image from wavelet transform
def reconstruct_wavelet(coeffs: list) -> np.ndarray:
   Reconstruct an image from the J-level wavelet approximation and_
 \hookrightarrow coefficients.
    Parameters:
    coeffs: list of the approximation and coefficients for each level
    R: 2D numpy array of the reconstructed image data
   R = coeffs[0] # Use last level approximation to start
    # Reconstruct the image
    for i in range(1,len(coeffs)):
        (cH, cV, cD) = coeffs[i]
        R = pywt.idwt2((R, (cH, cV, cD)), 'haar')
    return R
```

Problem 2b:

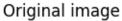
```
[21]: # Create initial PSNR and NNZ arrays
q = 9
PSNR = np.zeros((q+1,J+1))
NNZ = np.zeros((q+1,J+1))
```

```
# Create figure for original image
plt.figure()
plt.imshow(image, interpolation='none', cmap='gray')
plt.title('Original image')
plt.axis('off')
# Create figure for composite wavelet image
Coeffs = wavelet transform(image, J)
image_full = reconstruct_wavelet(Coeffs)
plt.figure()
plt.imshow(image_full, interpolation='none', cmap='gray')
plt.title(f'Reconstructed image full')
plt.axis('off')
# Calculate quantized wavelets
for n in range(q):
    Coeffs_temp = copy(Coeffs)
    for i in range (1,4):
        (cH, cV, cD) = Coeffs_temp[i]
        [cH, cV, cD] = quantize_pyramid([cH, cV, cD], 2**n, 0)
        Coeffs_temp[i] = (cH, cV, cD)
        NNZ[n,0] += (np.sum(cH != 0) + np.sum(cV != 0) + np.sum(cD != 0))
    image full = reconstruct wavelet(Coeffs temp)
    MSE = np.mean((image - image_full)**2) # Mean squared error
    PSNR[n,0] = 10*np.log10((255**2)/MSE) # Peak signal to noise ratio
# Plot PSNR and NNZ
plt.figure()
plt.plot(NNZ[:,0], PSNR[:,0])
plt.xlabel('NNZ')
plt.ylabel('PSNR')
plt.title('Level J=0')
# Create figure for level 1 wavelet image
Coeffs[-1] = tuple([np.zeros_like(v) for v in Coeffs[-1]])
image_1 = reconstruct_wavelet(Coeffs)
plt.figure()
plt.imshow(image_1, interpolation='none', cmap='gray')
plt.title(f'Reconstructed image 1')
plt.axis('off')
# Calculate quantized wavelets
for n in range(q):
    Coeffs_temp = copy(Coeffs)
    for i in range (1,4):
        (cH, cV, cD) = Coeffs_temp[i]
```

```
[cH, cV, cD] = quantize_pyramid([cH, cV, cD], 2**n, 0)
        Coeffs_temp[i] = (cH, cV, cD)
        NNZ[n,1] += (np.sum(cH != 0) + np.sum(cV != 0) + np.sum(cD != 0))
    image_full = reconstruct_wavelet(Coeffs_temp)
    MSE = np.mean((image - image_full)**2) # Mean squared error
    PSNR[n,1] = 10*np.log10((255**2)/MSE) # Peak signal to noise ratio
# Plot PSNR and NNZ
plt.figure()
plt.plot(NNZ[:,1], PSNR[:,1])
plt.xlabel('NNZ')
plt.ylabel('PSNR')
plt.title('Level J=1')
# Create figure for level 2 wavelet image
Coeffs[-2] = tuple([np.zeros_like(v) for v in Coeffs[-2]])
image_2 = reconstruct_wavelet(Coeffs)
plt.figure()
plt.imshow(image_2, interpolation='none', cmap='gray')
plt.title(f'Reconstructed image 2')
plt.axis('off')
# Calculate quantized wavelets
for n in range(q):
    Coeffs_temp = copy(Coeffs)
    for i in range (1,4):
        (cH, cV, cD) = Coeffs_temp[i]
        [cH, cV, cD] = quantize_pyramid([cH, cV, cD], 2**n, 0)
        Coeffs_temp[i] = (cH, cV, cD)
        NNZ[n,2] += (np.sum(cH != 0) + np.sum(cV != 0) + np.sum(cD != 0))
    image_full = reconstruct_wavelet(Coeffs_temp)
    MSE = np.mean((image - image_full)**2) # Mean squared error
    PSNR[n,2] = 10*np.log10((255**2)/MSE) # Peak signal to noise ratio
# Plot PSNR and NNZ
plt.figure()
plt.plot(NNZ[:,2], PSNR[:,2])
plt.xlabel('NNZ')
plt.ylabel('PSNR')
plt.title('Level J=2')
# Create figure for level 3 wavelet image
Coeffs[-3] = tuple([np.zeros_like(v) for v in Coeffs[-3]])
image_3 = reconstruct_wavelet(Coeffs)
plt.figure()
plt.imshow(image_3, interpolation='none', cmap='gray')
plt.title(f'Reconstructed image 3')
```

```
plt.axis('off')
# Calculate quantized wavelets
for n in range(q):
   Coeffs_temp = copy(Coeffs)
   for i in range(1,4):
        (cH, cV, cD) = Coeffs_temp[i]
        [cH, cV, cD] = quantize_pyramid([cH, cV, cD], 2**n, 0)
        Coeffs_temp[i] = (cH, cV, cD)
       NNZ[n,3] += (np.sum(cH != 0) + np.sum(cV != 0) + np.sum(cD != 0))
   image_full = reconstruct_wavelet(Coeffs_temp)
   MSE = np.mean((image - image_full)**2) # Mean squared error
   PSNR[n,3] = 10*np.log10((255**2)/MSE) # Peak signal to noise ratio
# Plot PSNR and NNZ
plt.figure()
plt.plot(NNZ[:,3], PSNR[:,3])
plt.xlabel('NNZ')
plt.ylabel('PSNR')
plt.title('Level J=3')
```

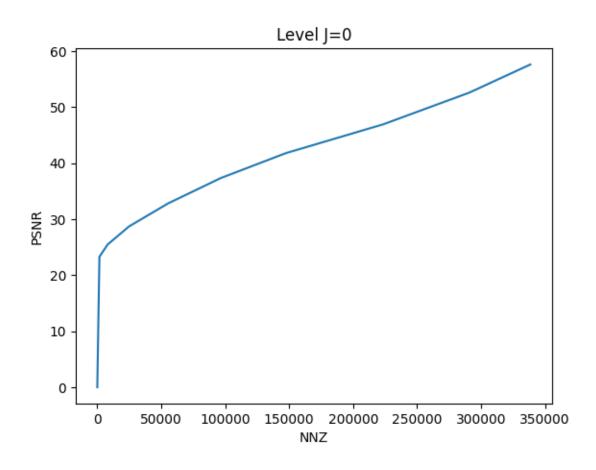
[21]: Text(0.5, 1.0, 'Level J=3')





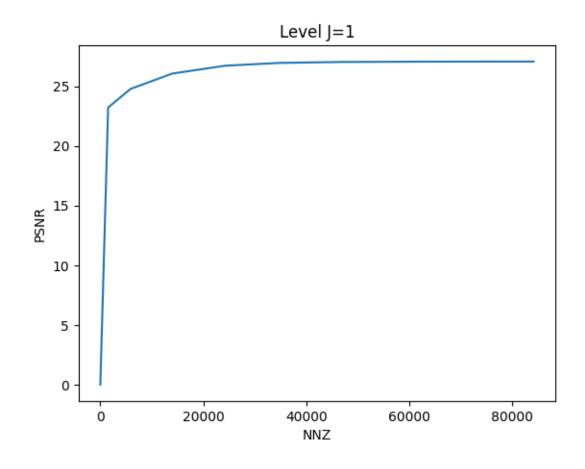
Reconstructed image full





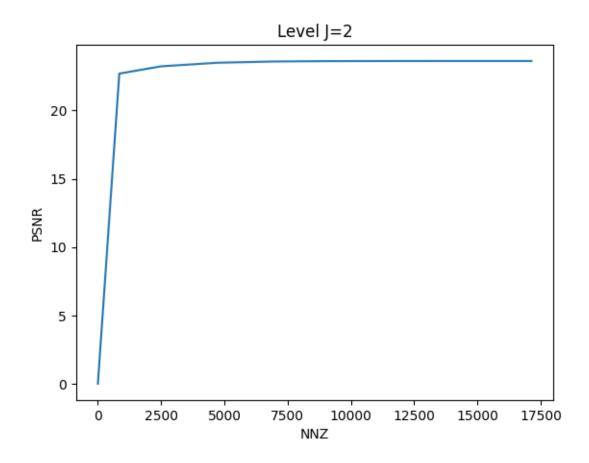
Reconstructed image 1





Reconstructed image 2





Reconstructed image 3



