Roll : 1603080 - B

Original Image :

In frequency domain filtering ,

We use low pass filtering to smoothen the image , keep low frequency components and remove noise.
G(u, v) = H(u, v) . F(u, v) is used for low passes with the radius of 10 , 30 and 60.

Code :

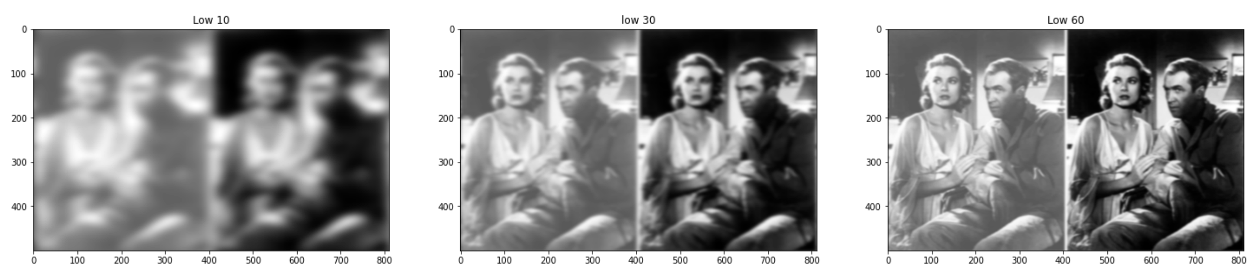
```
# -*- coding: utf-8 -*-
"""1603080_LabTest.ipynb

Automatically generated by Colaboratory.

Original file is located at

https://colab.research.google.com/drive/1M3_2n7-BDmBEj_Ean0DyGw4iDHMj2aAS
"""

from tensorflow.keras.preprocessing.image import load_img
from tensorflow.keras.preprocessing.image import img_to_array
from PIL import Image, ImageOps ,  ImageFilter
import matplotlib.pyplot as plt
import cv2
import numpy
import numpy as np
```

```
import math
import os
from PIL import Image

from imageio import imread
from google.colab.patches import cv2_imshow
```

```
#Low Filter in Frequency Domain using Gaussian method



def GaussianLowFilter(image,d):
   f = np.fft.fft2(image)
   fshift = np.fft.fftshift(f)
   s1 = np.log(np.abs(fshift))

   def make_transform_matrix(d):
       transfor_matrix = np.zeros(image.shape)
       center_point = tuple(map(lambda x:(x-1)/2,s1.shape))
       for i in range(transfor_matrix.shape[0]):
           for j in range(transfor_matrix.shape[1]):
               def cal_distance(pa,pb):
                   from math import sqrt
                   dis = sqrt((pa[0]-pb[0])**2+(pa[1]-pb[1])**2)
                   return dis
               dis = cal_distance(center_point,(i,j))
               transfor_matrix[i,j] = np.exp(-(dis**2)/(2*(d**2)))
       return transfor_matrix
   d_matrix = make_transform_matrix(d)
   new_img = np.abs(np.fft.ifft2(np.fft.ifftshift(fshift*d_matrix)))
   return new_img


img_l1 = GaussianLowFilter(img,10)
img_l2 = GaussianLowFilter(img,30)
img_l3 = GaussianLowFilter(img,60)


fig = plt.figure(figsize=(25,18))
```

```
ax  = fig.add_subplot(1,3,1)


plt.subplot(131)

plt.title('Low 10')
ax.imshow(img_l1,cmap="gray")


plt.subplot(132)

plt.title('low 30')
plt.imshow(img_l2,cmap="gray")

plt.subplot(133)

plt.title("Low 60")
plt.imshow(img_l3,cmap="gray")
plt.show()
```

Output :



And with high pass filtering we low frequency components and sharpen the image.
H(u, v) = 1 – H'(u, v) is used for highpasses with a radius of 10, 30,50.

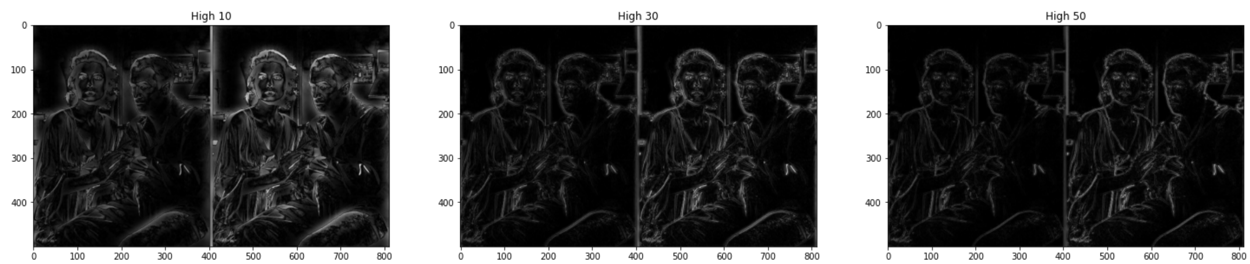
Code:

```
#High Filter in Frequency Domain using Gaussian method

def GaussianHighFilter(image,d):
   f = np.fft.fft2(image)
   fshift = np.fft.fftshift(f)
```

```
    s1 = np.log(np.abs(fshift))

    def make_transform_matrix(d):
        transfor_matrix = np.zeros(image.shape)
        center_point = tuple(map(lambda x:(x-1)/2,s1.shape))
        for i in range(transfor_matrix.shape[0]):
            for j in range(transfor_matrix.shape[1]):
                def cal_distance(pa,pb):
                    from math import sqrt
                    dis = sqrt((pa[0]-pb[0])**2+(pa[1]-pb[1])**2)
                    return dis
                dis = cal_distance(center_point,(i,j))  #calculate distance
from center point
                transfor_matrix[i,j] = 1-np.exp(-(dis**2)/(2*(d**2)))
        return transfor_matrix
    d_matrix = make_transform_matrix(d)
    new_img = np.abs(np.fft.ifft2(np.fft.ifftshift(fshift*d_matrix)))
    return new_img




img_h1 =GaussianHighFilter(img,10)
mg_h1 =GaussianHighFilter(img,30)
mg_h1 =GaussianHighFilter(img,50)

fig = plt.figure(figsize=(25,18))
ax  = fig.add_subplot(1,3,1)


plt.subplot(131)

plt.title('High 10')
plt.imshow(img_h1,cmap="gray")


plt.subplot(132)

plt.title('High 30')
plt.imshow(img_h2,cmap="gray")
```

```
plt.subplot(133)

plt.title("High 50")
plt.imshow(img_h3,cmap="gray")

plt.show()
```

Output :



Used Gaussian filtering methods for both high and low filtering in the frequency domain.

Spatial filtering technique :

Smoothing Spatial Filter: Smoothing filter is used for blurring and noise reduction in the image. Blurring is pre-processing steps for removal of small details and Noise Reduction is accomplished by blurring.
Here, **median filtering** has been used for smoothening.

Code :

```
#Smoothing Image Using Median Filtering



def median_filter(data, filter_size):
   temp = []
   indexer = filter_size // 2
   data_final = []
   data_final = numpy.zeros((len(data),len(data[0])))
   for i in range(len(data)):
```

```
       for j in range(len(data[0])):

           for z in range(filter_size):
               if i + z - indexer < 0 or i + z - indexer > len(data) - 1:
                   for c in range(filter_size):
                       temp.append(0)
               else:
                   if j + z - indexer < 0 or j + indexer > len(data[0]) -
1:

                       temp.append(0)
                   else:
                       for k in range(filter_size):
                           temp.append(data[i + z - indexer][j + k -
indexer])

           temp.sort()
           data_final[i][j] = temp[len(temp) // 2]
           temp = []
   return data_final

def main():
   img = Image.open("/content/final_pic.jpg").convert("L")
    arr = numpy.array(img)
   removed_noise = median_filter(arr, 3)
   img1 = Image.fromarray(removed_noise)
   plt.imshow(img1)
   img.show()

main()
```

Output :

For sharpening in the spatial domain , first order, and second order derivatives have been used.

f' = f(x+1) - f(x)
f'' = f(x+1) + f(x-1) - 2f(x)

Code :

```
#Sharpening Image in Spatial Filtering Using First Order and Second Order Derivative



filter1=1.1
filter2=-0.1


def sharpen2(photo,height,width,filter1,filter2):
```

```
    for y in range(1,height-1):
        for x in range(1,width-1):

            (r,g,b)=photo.getpixel((x,y))
            r=int(r*filter1)
            g=int(g*filter1)
            b=int(b*filter1)

            (r1,g1,b1)=photo.getpixel((x-1,y-1))
            r1=int(r1*filter2)
            g1=int(g1*filter2)
            b1=int(b1*filter2)

            (r2,g2,b2)=photo.getpixel((x,y-1))
            r2=int(r2*filter2)
            g2=int(g2*filter2)
            b2=int(b2*filter2)

            (r3,g3,b3)=photo.getpixel((x+1,y-1))
            r3=int(r3*filter2)
            g3=int(g3*filter2)
            b3=int(b3*filter2)

            (r4,g4,b4)=photo.getpixel((x-1,y))
            r4=int(r4*filter2)
            g4=int(g4*filter2)
            b4=int(b4*filter2)

            (r5,g5,b5)=photo.getpixel((x+1,y))
            r5=int(r5*filter2)
            g5=int(g5*filter2)
            b5=int(b5*filter2)

            (r6,g6,b6)=photo.getpixel((x-1,y+1))
            r6=int(r6*filter2)
            g6=int(g6*filter2)
            b6=int(b6*filter2)

            (r7,g7,b7)=photo.getpixel((x,y+1))
            r7=int(r7*filter2)
```

```
            g7=int(g7*filter2)
            b7=int(b7*filter2)

            (r8,g8,b8)=photo.getpixel((x+1,y+1))
            r8=int(r8*filter2)
            g8=int(g8*filter2)
            b8=int(b8*filter2)

            rfPixel=r+r1+r2+r3+r4+r5+r6+r7+r8
            if rfPixel>255:
                rfPixel=255
            elif rfPixel<0:
                rfPixel=0

            gfPixel= g+g1+g2+g3+g4+g5+g6+g7+g8
            if gfPixel>255:
                gfPixel=255
            elif gfPixel<0:
                gfPixel=0

            bfPixel=b+b1+b2+b3+b4+b5+b6+b7+b8
            if bfPixel>255:
                bfPixel=255
            elif bfPixel<0:
                bfPixel=0

            photo.putpixel((x,y),(rfPixel,gfPixel,bfPixel))
    return photo


photo=Image.open("/content/final_pic.jpg").convert("RGB")
photo2=photo.copy()
height=photo.height
width=photo.width
x=sharpen2(photo,height,width,filter1,filter2)



plt.imshow(x)
```

Output :

The biggest advantage that one gets in the frequency domain is speed, if the size of the spatial filter is big (say > 3 x 3). In frequency domain spatial convolution boils down to simple multiplication.

Some of the advantages and disadvantages are :
First, some spatial filters accomplish results identical to those implemented in the frequency domain, without the overhead of spatial-to-frequency conversion and back.

Second, many images do not benefit from having the same (frequency) filter applied everywhere. In order for a frequency filter to be applied only to selected localities, complex transformation is wanted, effectively doubling the filtering workload.

While frequency domain filters can be simpler than their spatial domain equivalents, doubling (buffer thrashing) overhead for applying simpler filters can outweigh complexity cost for equivalent spatial filters whose instructions can stay cached.