IMAGE ENHANCEMENT



Digital signal processing Sem-Project

Presented by: (Group 12)

- Neha Mahindrakar(18BEC032)
- ☐ Nikhil SA(18BEC033)
- Nithin Rangineni(18BEC034)

Image enhancement is the procedure of improving the quality and information content of a digital image.

In other words, sharpening, deblurring or brightening an image is its enhancement.







The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide 'better' input for other automated image processing techniques.

They are used in Aerial imaging, Satellite imaging, Medical imaging, Digital camera application, Remote sensing etc. Image processing techniques are broadly classified into two major methods. They are:

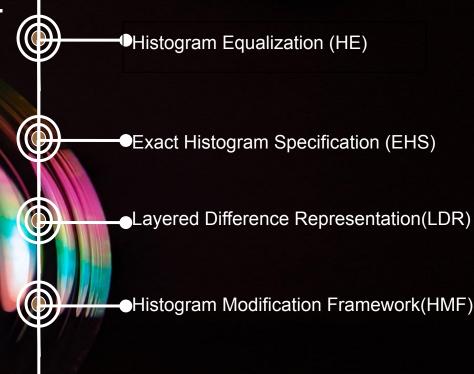
SPATIAL DOMAIN METHODS Includes direct_manipulation_on pixels of an image. The two main approaches include 1.Point processing 2. Neighbourhood Operations

FREQUENCY DOMAIN METHODS

We compute the fourier transform of the image to be enhanced, multiply the result by a filter and take the inverse transform to produce the enhanced image.

1.Histogram Processing:

This includes Spatial domain methods taking into account a histogram of an overall / part of an pixels of an image, processing is done.

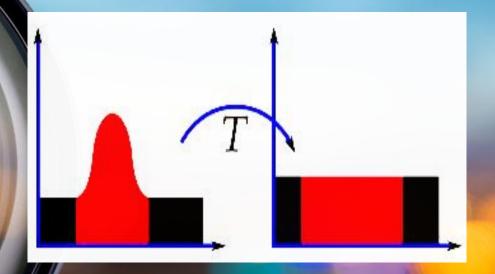


Contextual and Variational

Enhancement(CVC)

Histogram Equalization:

Histogram Equalization is an image processing technique that adjusts the contrast of an image by using its histogram. To enhance the image's contrast, it spreads out the most frequent pixel intensity values or stretches out the intensity range of the image. By accomplishing this, histogram equalization allows the image's areas with lower contrast to gain a higher contrast.



Why do we need Histogram equalization?

Histogram Equalization can be used when you have images that look washed out because they do not have sufficient contrast. In such photographs, the light and dark areas blend together creating a flatter image that lacks highlights and shadows.

A key advantage of the method is that it is a fairly straightforward technique and an invertible operator. So in theory, if the histogram equalization function is known, then the original histogram can be recovered. The calculation is not computationally intensive.



Code:

```
import cv2 as cv
import numpy as np
from matplotlib import pyplot as plt
path = "_____"
img = cv.imread(path)
cv.imshow('image',img)
hist,bins = np.histogram(img.flatten(),256,[0,256])
```

```
plt.hist(img.flatten(),256,[0,256], color = 'r')
plt.xlim([0,256])
plt.legend(('histogram'), loc = 'upper left')
plt.show()
R, G, B = \text{cv.split(img)}
output 1 R = \text{cv.equalizeHist}(R)
output 1 G = \text{cv.equalizeHist}(G)
output1_B = cv.equalizeHist(B)
```

equ = cv.merge((output1 R, output1 G, output1 B))

hist, bins = np.histogram(equ.flatten(), 256, [0, 256])

cv.imshow('equ.png',equ)

```
plt.hist(equ.flatten(),256,[0,256], color = 'r')
plt.xlim([0,256])
plt.legend(('histogram'), loc = 'upper left')
plt.show()
```

The general histogram equalization formula is:

$$h(v) = round \left(\frac{cdf(v) - cdf_{min}}{(M*N) - cdf_{min}} * (L-1) \right)$$

Where:

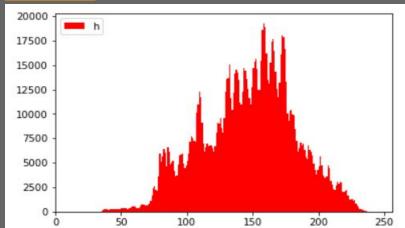
- $\gt cdf_{min}$ The minimum value of the *cdf*
- > M * N: image's number of pixels. (M-width, N-height)
- L -number of gray scale levels (in most cases, 255).

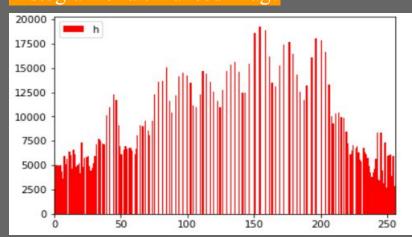


Output Image



Histogram



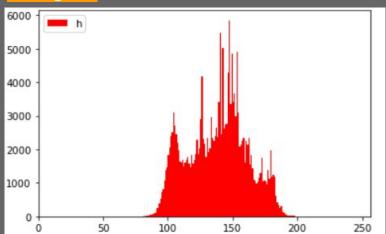


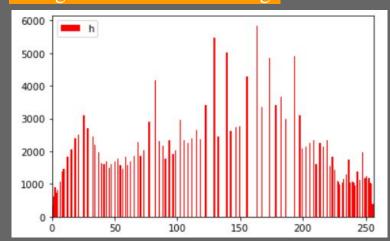


Output Image



Histogram



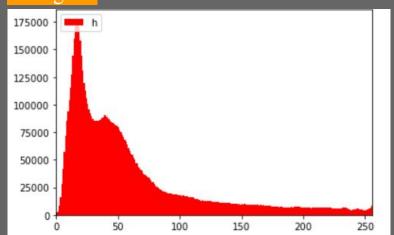


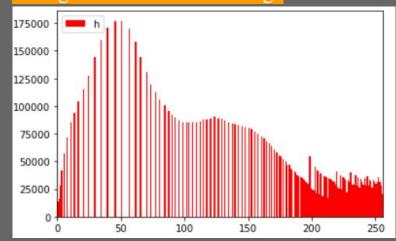


Output Image



Histogram



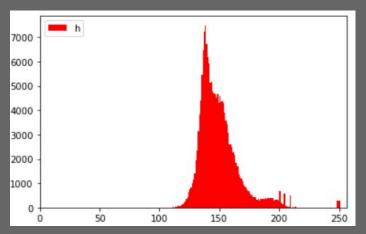


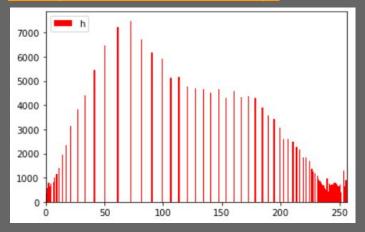


Output Image



Histogram







Output Image



Histogram

