ज्ञानेन विकासः

DIGITAL SIGNAL PROCESSING(EC306)

PROJECT REPORT - IMAGE ENHANCEMENT

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Introduction

Image enhancement is the procedure of improving the quality and information content of original data before processing. Common practices include contrast enhancement, spatial filtering, density slicing, and FCC. Contrast enhancement or stretching is performed by linear transformation expanding the original range of gray level. Spatial filtering improves the naturally occurring linear features like fault, shear zones, and lineaments. Density slicing converts the continuous gray tone range into a series of density intervals marked by a separate color or symbol to represent different features.

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.

Image enhancement techniques can be divided into two broad categories:

1.Spatial domain methods, which operate directly on pixels, and
2.Frequency domain methods, which operate on the Fourier transform of an image.

Literature survey

Image enhancement, one of the image pre-processing images is the procedure of improving the quality and information content of a digital image .

In other words improving noise, 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.

The Literature survey report can be found in Report (Report) and PPT(PPT).

Overview of the algorithm:

Histogram Equalization

This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

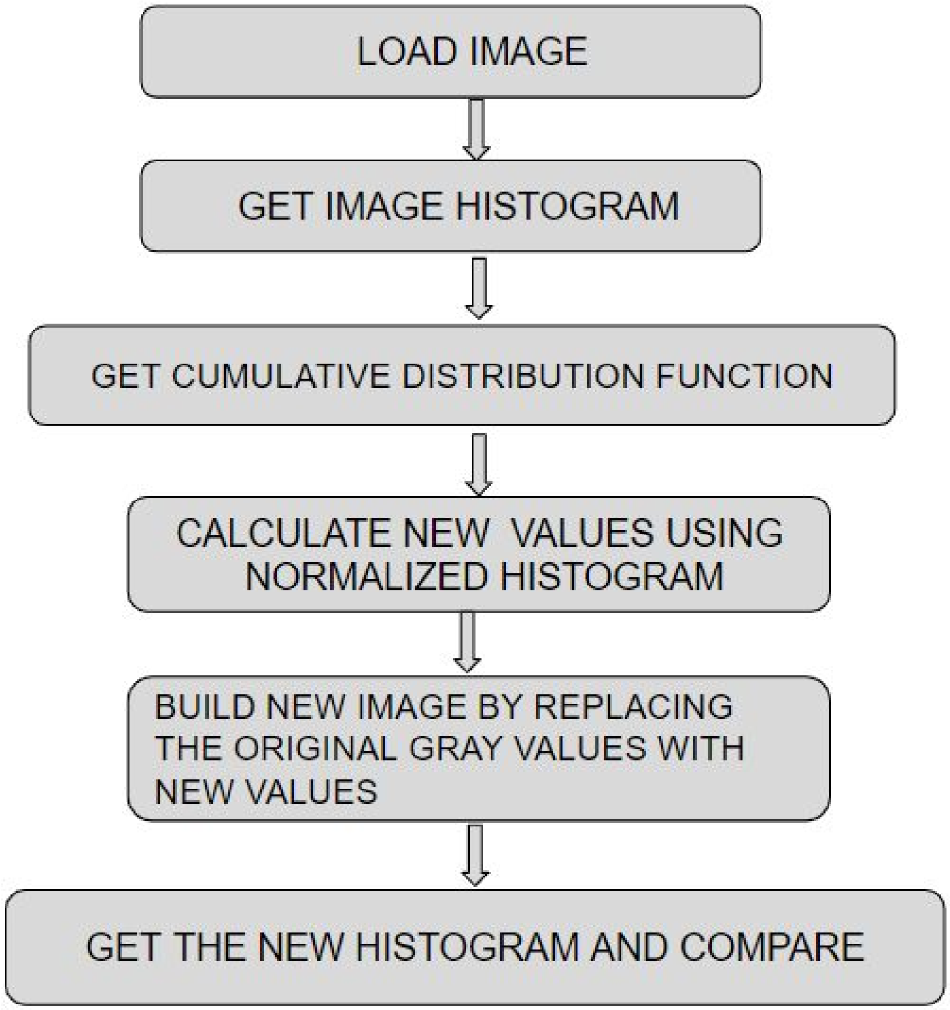
The method is useful in images with backgrounds and foregrounds that are both bright or both dark. In particular, the method can lead to better views of bone structure in x-ray images, and to better detail in photographs that are over or under-exposed. A key advantage of the method is that it is a fairly 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. A disadvantage of the method is that it is indiscriminate. It may increase the contrast of background noise, while decreasing the usable signal.

In scientific imaging where spatial correlation is more important than intensity of signal (such as separating DNA fragments of quantized length), the small signal to noise ratio usually hampers visual detection.

Histogram equalization often produces unrealistic effects in photographs; however it is very useful for scientific images like thermal, satellite or x-ray images, often the same class of images to which one would apply false-color. Also histogram equalization can produce undesirable effects (like visible image gradient) when applied to images with low color depth. For example, if applied to an 8-bit image displayed with an 8-bit gray-scale palette it will further reduce color depth (number of unique shades of gray) of the image. Histogram equalization will work the best when applied to images with much higher color depth than palette size, like continuous data or 16-bit gray-scale images.

PPT that includes details of the method for HE.

FLOWCHART:

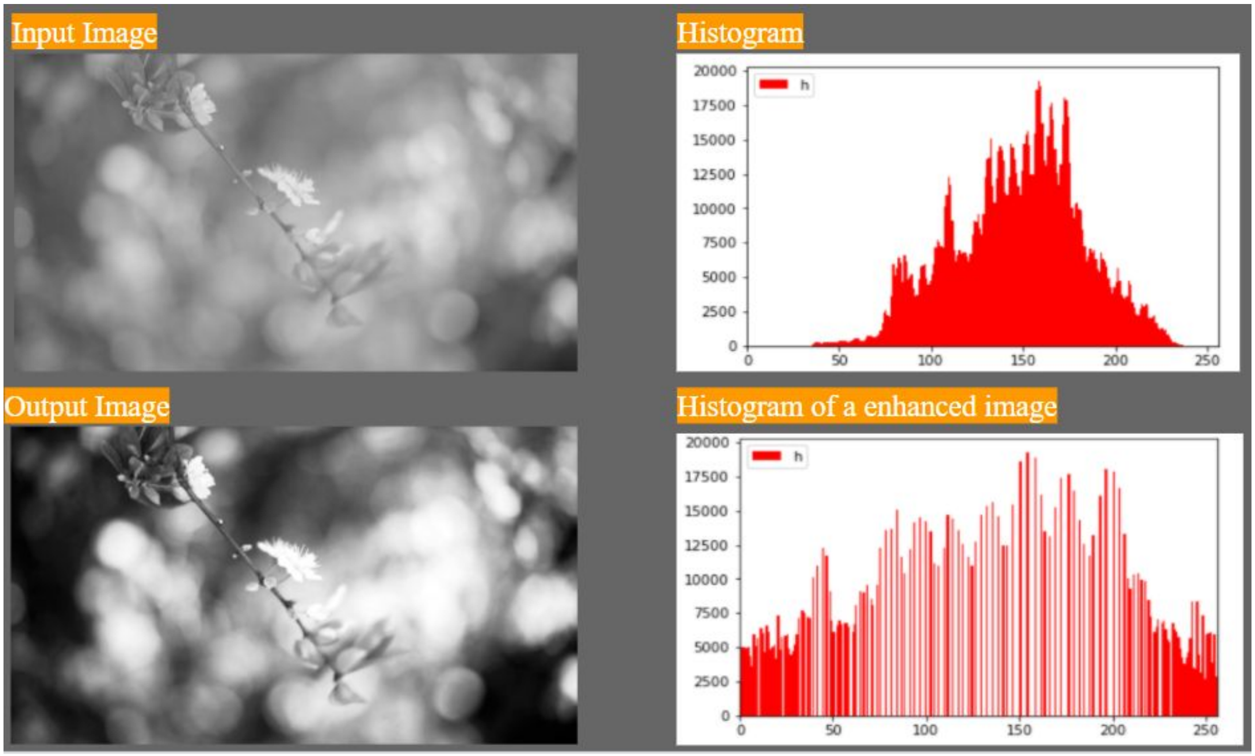


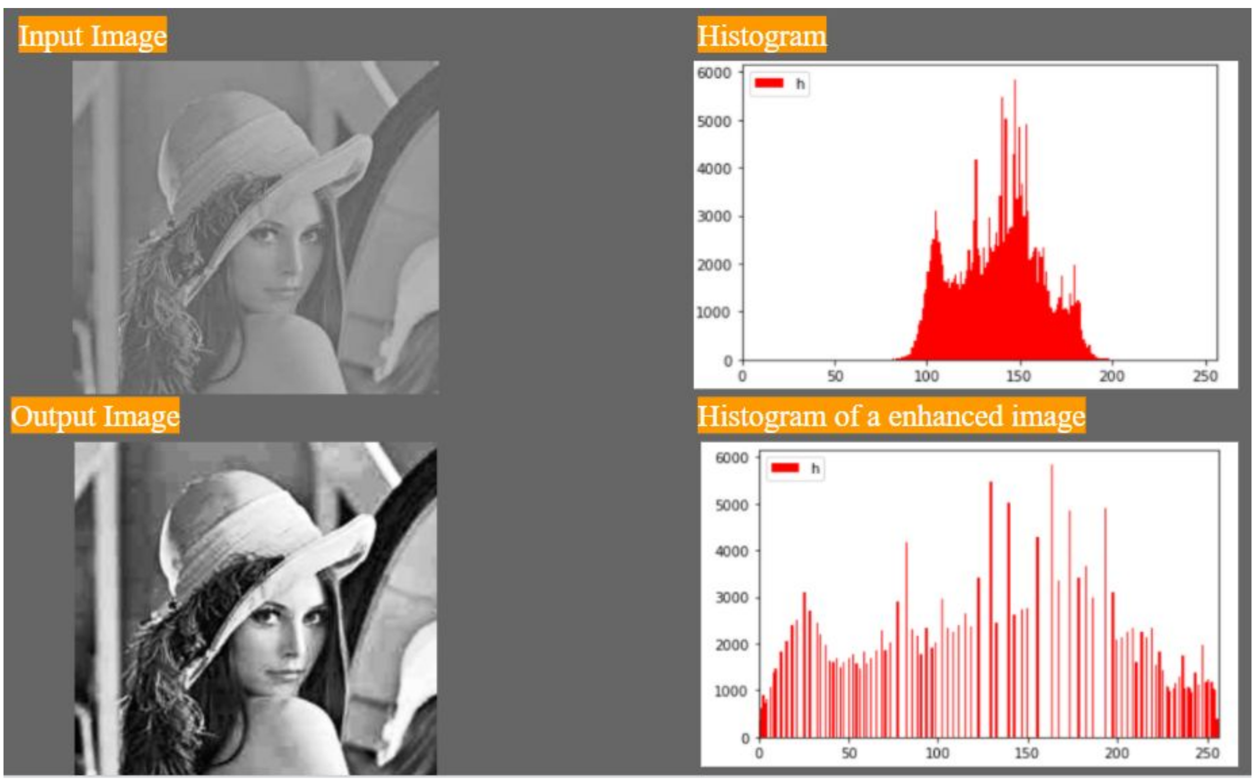
PROGRAM:

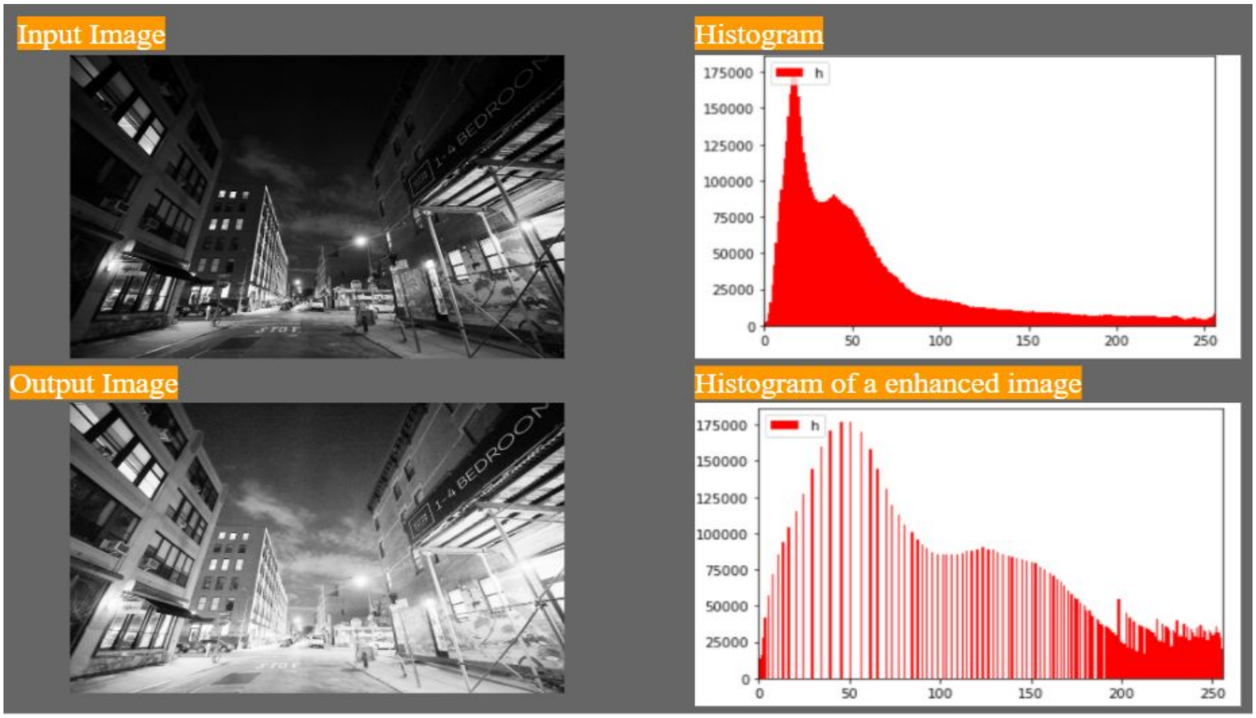
```
import cv2 as cv

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])

cdf = hist.cumsum()

cdf_normalized = cdf * float(hist.max()) / cdf.max()
plt.plot(cdf_normalized, color = 'b')
plt.hist(img.flatten(),256,[0,256], color = 'r')
plt.xlim([0,256])
plt.legend(('cdf','histogram'), loc = 'upper left')
plt.show()
R, G, B = cv.split(img)
output1_R = cv.equalizeHist(R)
output1_G = cv.equalizeHist(G)
```

```
output1_B = cv.equalizeHist(B)
equ = cv.merge((output1_R, output1_G, output1_B))
cv.imshow('equ.png',equ)
hist,bins = np.histogram(equ.flatten(),256,[0,256])
cdf = hist.cumsum()
cdf_normalized = cdf * float(hist.max()) / cdf.max()
```

Results:


Input Image
Histogram
h
Output Image
Histogram of a enhanced image
h


Input Image
Histogram
h
Output Image
Histogram of a enhanced image
h


Input Image
Histogram
175000
150000
125000
100000
75000
50000
25000
0
0
50
100
150
200
250
h
Output Image
Histogram of a enhanced image
175000
150000
125000
100000
75000
50000
25000
0
0
50
100
150
200
250
h

Conclusion:

There are two ways to think about and implement histogram equalization, either as image change or as palette change. The operation can be expressed as *P(M(I))* where *I* is the original image, *M* is histogram equalization mapping operation and *P* is a palette. If we define a new palette as *P'=P(M)* and leave image *I* unchanged then histogram equalization is implemented as palette change. On the other hand, if palette P remains unchanged and image is modified to *I'=M(I)* then the implementation is by image change. In most cases palette change is better as it preserves the original data.

Modifications of this method use multiple histograms, called sub histograms, to emphasize local contrast, rather than overall contrast. Examples of such methods include adaptive histogram equalization, *contrast limited adaptive histogram equalization* or CLAHE, multipeak histogram equalization (MPHE), and multipurpose beta optimized bihistogram equalization (MBOBHE). The goal of these methods, especially MBOBHE, is to improve the contrast without producing brightness mean-shift and detail loss artifacts by modifying the HE algorithm.

A signal transform equivalent to histogram equalization also seems to happen in biological neural networks so as to maximize the output firing rate of the neuron as a function of the input statistics. This has been proved in particular in the fly retina.

Histogram equalization is a specific case of the more general class of histogram remapping methods. These methods seek to adjust the image to make it easier to analyze or improve visual quality (e.g., retinex)

References:

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3.www.ejournal.aessangli.in/ASEEJournals/EC46.pdf

4.www.researchgate.net/publication/284015115_Mathematical_Equations_for_Homomorphic_Filtering_in_Frequency_Domain_A_Literature_Survey