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Image Engineering Fundamentals  
*Final Report*

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## Problem 1

For this problem, I made use of the OpenCV library in Python for carrying out the necessary normalization and enhancements.

Before we continue into each of the solutions I would like to share and explain my general code for performing the normalized cumulative histogram processing.

```
import cv2
import numpy as np
from matplotlib import pyplot as plt
import sys

inputf = sys.argv[1]
outputf = sys.argv[2]

# reading the greyscale image through OpenCV
input_1 = cv2.imread(inputf,0)

print("Input1: Gray level values in pixels")
for i in range (input_1.shape[0]): #traverses through height of the image
    for j in range (input_1.shape[1]): #traverses through width of the image
        print(input_1[i][j], end="\t")
    print("\n")

# calculating the cumulative distribution function (cdf)
def cdf_calc(image):
    # generating the histogram by flattening the image through NumPy
    hist,bins = np.histogram(image.flatten(),256,[0,256])

    # Cumulative Distribution function of the Histogram
    cdf = hist.cumsum()

    # Calculating the normalized cumulative histogram
    cdf_normalized = cdf * float(hist.max()) / cdf.max()

    return cdf, cdf_normalized

# cdf and normalized cdf for the input image
cdf, cdf_normalized = cdf_calc(input_1)

# plotting the histogram of the input image
plt.subplot(121)
plt.title("Input Image 1")
plt.plot(cdf_normalized, color = 'b')
plt.hist(input_1.flatten(),256,[0,256], color = 'r')
plt.xlim([0,256])
plt.legend(('cdf','histogram'), loc = 'upper right')

# normalized cumulative histogram (cdf) is used as a mapping function
# utilized the mapping arrays of NumPy for this purpose
cdf_m = np.ma.masked_equal(cdf,0)
cdf_m = (cdf_m - cdf_m.min())*255/(cdf_m.max()-cdf_m.min())
cdf = np.ma.filled(cdf_m,0).astype('uint8')
```

## Normalized Cumulative Histogram Processing (1/2)

```

# output image gray values are calculated putting the input image inside the new cdf
output_1 = cdf[input_1]
# the new image is written out as result_1.png
cv2.imwrite(outputf, output_1)

# calculating the cdf and cdf_normalized values for plotting the histogram of output image
cdf1, cdf_normalized1 = cdf_calc(output_1)

print("Output1: Gray level values in pixels")
for i in range (output_1.shape[0]): #traverses through height of the image
    for j in range (output_1.shape[1]): #traverses through width of the image
        print(output_1[i][j], end="\t")
    print("\t")

# plotting the histogram of the output image
plt.subplot(122)
plt.title("Output Image 1")
plt.plot(cdf_normalized1, color = 'b')
plt.hist(output_1.flatten(),256,[0,256], color = 'r')
plt.xlim([0,256])
plt.legend(('cdf','histogram'), loc = 'upper right')

# printing the final graphs
plt.show()

```

## Normalized Cumulative Histogram Processing (2/2)

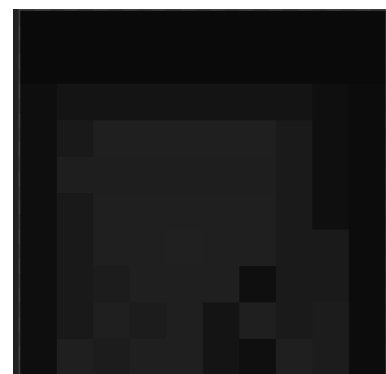
I utilized the above libraries and Numpy for carrying out my calculations, the relevant steps are explained with comments.

### (1) Result of contrast enhancement is good.

For this example I took the following as the our input image. I generated this 10x10 image with a varying gray-level range as follows.

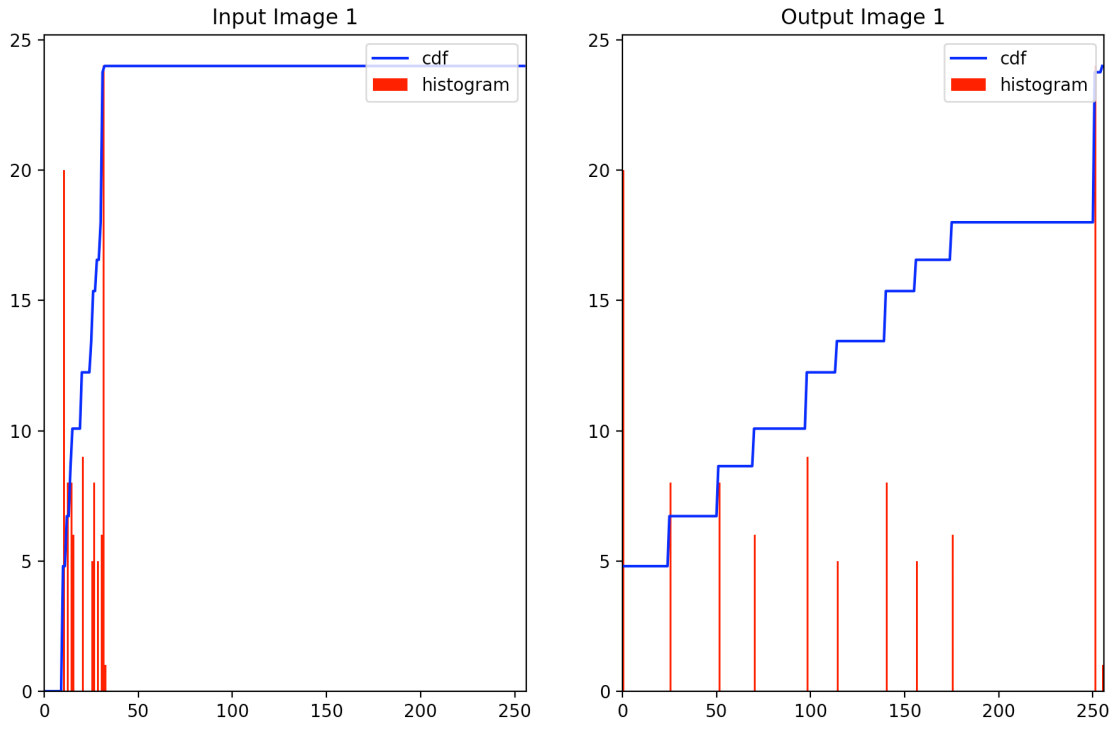
Input1: Gray level values in pixels									
10	10	10	10	10	10	10	10	10	10
10	10	10	10	10	10	10	10	10	10
14	20	20	20	20	20	20	20	15	12
14	25	31	31	31	31	31	26	15	12
14	30	30	30	30	30	30	26	15	12
14	25	31	31	31	31	31	26	15	12
14	25	31	31	32	31	31	26	26	12
14	25	28	31	31	31	15	26	26	12
14	25	31	28	31	20	31	26	28	12
14	31	28	31	31	20	15	31	28	12

Gray level values per pixel for the 10x10 image



Input 10x10 image

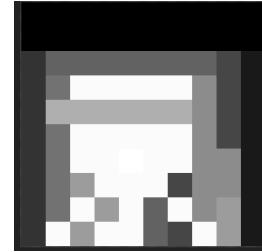
After passing the image through the above program, the following gray-level and cumulative gray-level histograms were generated.



**Cumulative gray-level and gray-level histograms for the input and output image.**

Finally, after performing the contrast enhancement the resulting output image and its pixel detail is as follows.

Output1: Gray level values in pixels									
0	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	0
51	98	98	98	98	98	98	98	70	25
51	114	251	251	251	251	251	140	70	25
51	175	175	175	175	175	175	140	70	25
51	114	251	251	251	251	251	140	70	25
51	114	251	251	255	251	251	140	140	25
51	114	156	251	251	251	70	140	140	25
51	114	251	156	251	98	251	140	156	25
51	251	156	251	251	98	70	251	156	25



**Gray level values per pixel for the 10x10 enhanced output image**

**Output 10x10 image after enhancement**

As observed in the source code attached above, for the histogram equalization the following methods were utilized.

The cumulative distribution function, cdf was first calculated as follows: (which is also the image's accumulated normalized histogram).

$$cdf_x(i) = \sum_{j=0}^i p_x(x = j),$$

Then using a masking function, cdf\_m, in the following form, we then replace it back in the cdf to generate the output image.

$$cdf_m = \frac{cdf_m - \min(cdf_m)}{\max cdf_m - \min cdf_m} * 255$$

Results: In this scenario, the technique works well as the gray levels are relatively spread out and as a result increasing the contrast, enhances the details and we get a relatively good result.

## (2) Result of enhancement is bad

For an example of bad enhancement, I deliberately made an image with relatively narrower gray level range as follows:

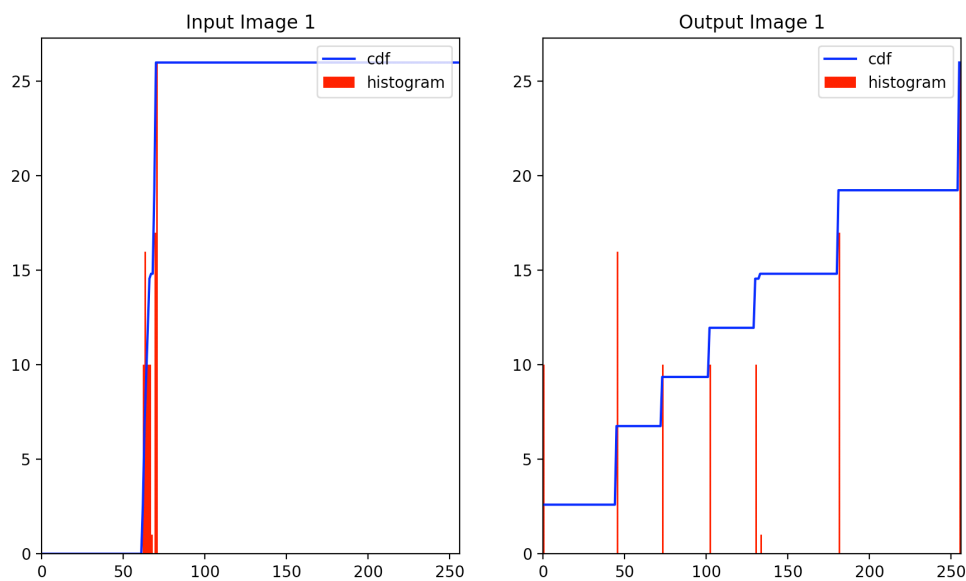
Input1: Gray level values in pixels									
64	70	70	70	63	70	70	70	70	64
64	70	63	63	63	63	63	70	70	64
64	70	70	70	70	70	70	70	70	64
64	70	63	63	63	63	63	70	70	64
64	70	70	63	67	62	70	70	70	64
62	62	63	62	63	62	62	62	62	62
69	69	63	69	63	69	62	69	69	69
66	66	66	66	66	66	66	66	66	66
69	69	69	69	69	69	69	69	69	69
65	65	65	65	65	65	65	65	65	65

The gray pixel values for input image 2



Input image 2

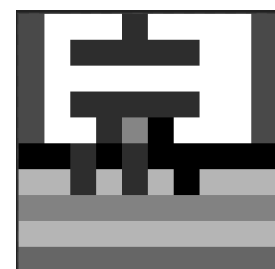
After performing the contrast enhancement on this set of image, the results were as follows:



With the resulting output image and the pixels being:

Output1: Gray level values in pixels									
73	255	255	255	45	255	255	255	255	73
73	255	45	45	45	45	45	255	255	73
73	255	255	255	255	255	255	255	255	73
73	255	45	45	45	45	45	255	255	73
73	255	255	45	133	0	255	255	255	73
0	0	45	0	45	0	0	0	0	0
181	181	45	181	45	181	0	181	181	181
130	130	130	130	130	130	130	130	130	130
181	181	181	181	181	181	181	181	181	181
102	102	102	102	102	102	102	102	102	102

Gray pixel values for output image 2



The resulting image as output2

Result: Unlike the previous turn we had much closer gray levels and hence by the nature of the contrast enhancement we see a lot of extreme results, in which the detail of the foreground is lost or merged and there is increase in noise as well.

Therefore this method of contrast enhancement with histogram equalization has its advantages and disadvantages and hence must be used depending on the type of the problem.

## Problem 4

(1) In a 2-dimensional space, I chose the following points for the exercise:

$$C_1(2,3), C_2(5,8), C_3(8,2)$$

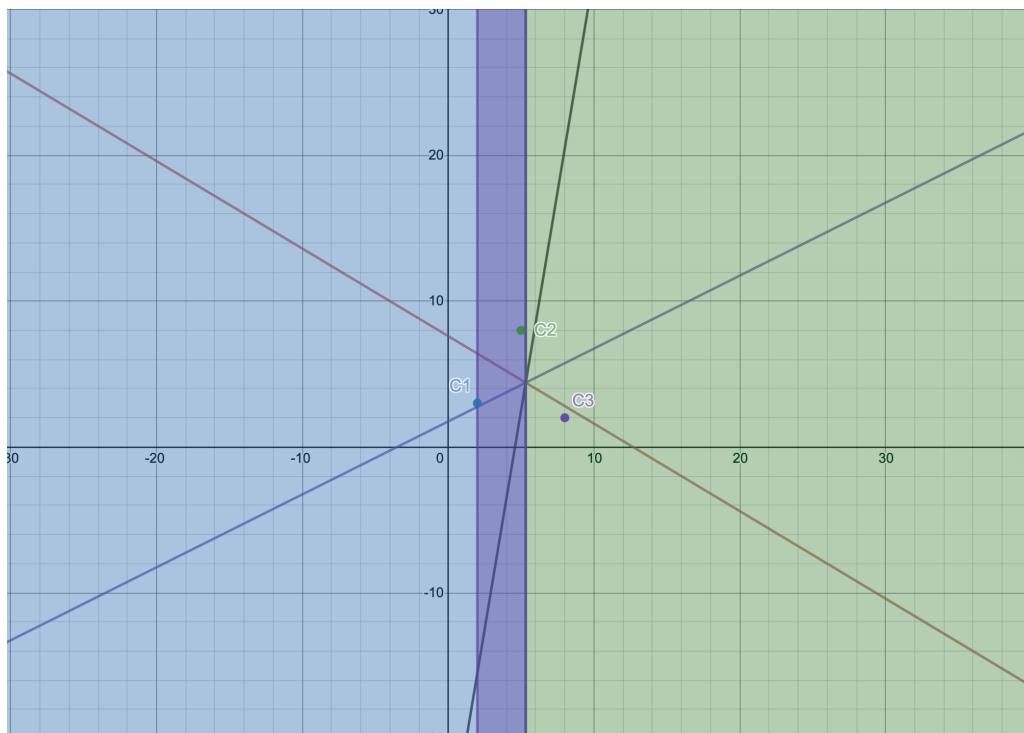
The equations for their decision boundaries are lines which are perpendicular to the line joining every two of these points while also passing their mid-points.

For  $C_1$  and  $C_2$ : Line with slope  $-3/5$  and passing through midpoint  $(3.5, 5.5)$ .  $y = \frac{-3}{5}x + 7.6$  ( $x \leq 5.318$ )

For  $C_2$  and  $C_3$ : Line with slope  $1/2$  and passing through midpoint  $(6.5, 5)$ .  $y = \frac{1}{2}x + 1.75$  ( $x \geq 5.318$ )

For  $C_3$  and  $C_1$ : Line with slope  $6$  and passing through midpoint  $(5, 2.5)$ .  $y = 6x - 27.5$  ( $2 \leq x \leq 5.318$ )

On a graph they are plotted as follows.



(2) For each of the above three categories in the Nearest Neighbor rule, an input pattern can be classified as follows based on the shortest Euclid distance from each of the categories.

- a.  $C_1 \rightarrow (-4,4) (\sqrt{37})$
- b.  $C_2 \rightarrow (2,8) (3)$
- c.  $C_3 \rightarrow (10,4) (2\sqrt{2})$

(3) The three categories above are classified as prototypes  $\omega_i$  ( $i = 1,2,3$ ) while the input pattern is an 2-d vector  $x = (x_1, x_2)$ .

For each of the classes, we give the a-priori probabilities  $P(\omega_1) = P(\omega_2) = P(\omega_3) = \frac{1}{3}$ .

We can assume an a-prior density function to be, say, the Gaussian Distribution.

$$\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}$$

$$p(x | \omega_1) = \phi(x) \text{ (} x \leq 5.318 \text{); } = 0 \text{ otherwise}$$

$$p(x | \omega_1) = \phi(x) \text{ (} 2 \leq x < 5.318 \text{); } 0 \text{ otherwise}$$

$$p(x | \omega_1) = \phi(x) \text{ (} 0 < x > 5.318 \text{); } 0 \text{ otherwise}$$