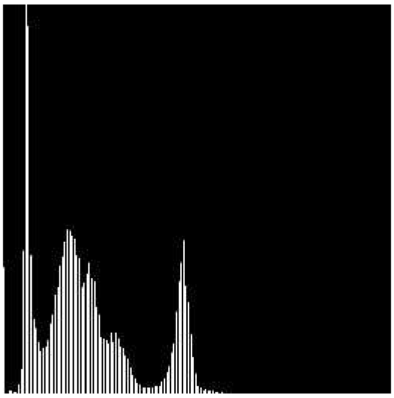
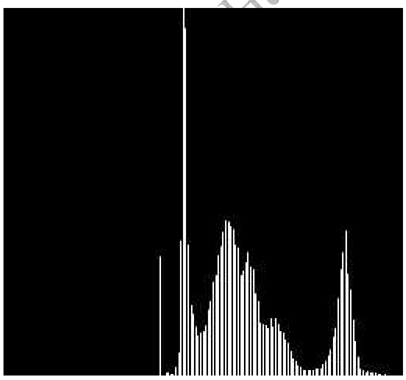
Original image



Histogram of original image

Image after positive-value histogram sliding



Histogram of image after sliding

Figurer (2.21): Histogram Sliding.

2. 10 <u>Histogram Equalization</u>

Is a popular technique for improving the appearance of a poor image. It's a function is similar to that of a histogram stretch but often provides more visually pleasing results a cross a wide rang of images.

Histogram equalization is a technique where the histogram of the resultant image is <u>as flat as possible (with histogram stretching the overall shape of the histogram remains the same).</u>

The results in a histogram with a mountain grouped closely together to "spreading or flatting histogram makes the dark pixels appear darker and the light pixels appear lighter (the key word is "appear" the dark pixels in a photograph can not by any darker. If, however, the pixels that are only slightly lighter become much lighter, then the dark pixels will appear darker).

The histogram equalization process for digital images consists of four steps:

1. Find the running sum of the histogram values
2. Normalize the values from step1 by dividing by total number of pixels.
3. Multiply the values from step2 by the maximum gray level value and round.
4. Map the gray-level values to the results from step 3, using a one-to-one correspondence. The following example will help to clarify this process.

<u>Example</u>:-

We have an image with 3 bit /pixel, so the possible range of values is 0 to 7. We have an image with the following histogram:

Gray-level value	0	1	2	3	4	5	6	7
No of Pixel Histogram value	10	8	9	2	14	1	5	2

Step 1: Great a running sum of histogram values. This means that the first values is 10, the second is 10+8=18, next is 10+8+9=27, and soon. Here we get 10,18,29,43,44,49,51.

Step 2: Normalize by dividing by total number of pixels. The total number of pixels is 10+8+9+2+14+1+5+0=51.

Step 3 : Multiply these values by the maximum gray – level values in this case 7 , and then round the result to the closet integer. After this is done we obtain 1,2,4,4,6,6,7,7.

Step 4 : Map the original values to the results from step3 by a one –to-one correspondence.

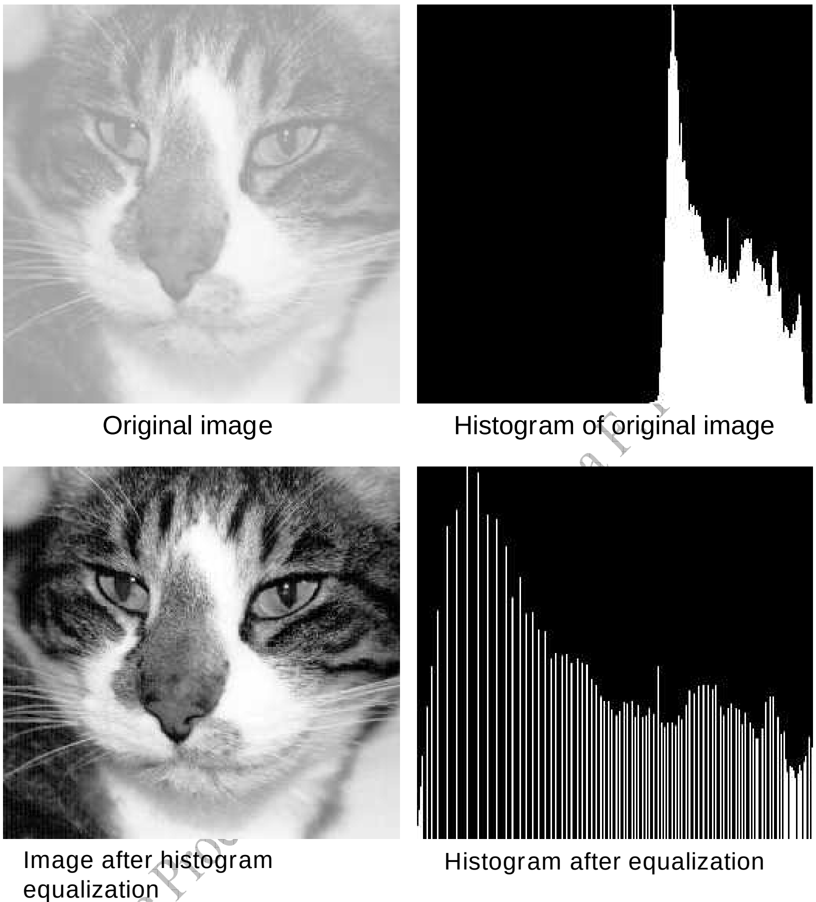
The first three steps:

Gray-level	0	1	2	3	4	5	6
No. of Pixel	10	8	9	2	14	1	5
Run Sum	10	18	27	29	43	44	49
Normalized	10/51	18/51	27/51	29/51	43/51	44/51	49/51
Multiply by 7	1	2	4	4	6	6	7

The fourth step:

Old	0	1	2	3	4	5	6	7
New	1	2	4	4	6	6	7	7

All pixel in the original image with gray level 0 are set to 1, values of 1 are set to 2, 2 set to 4, 3 set to 4, and so on (see figure (2-21)) histogram equalization, you can see the original histogram and the resulting histogram equalized histogram. Although the result is not flat, it is closer to being flat than the original.



Figurer (2.21): Histogram Equalization.

2.11 Histogram features

The histogram features that we are considered are statically based features where the histogram is used as a model of the probability distribution of the gray levels. These statistical features provide us with information a bout the characteristic of the gray – level distribution for the image or sub image. We define the **first – order histogram probability P(a)** as :

$$P(g) = \frac{N(g)}{M}$$

M is the number of pixels in the image or sub image (if the entire image is under consideration, then M= N^2 for N×N), and N (g) is the number of pixels at gray level g. as with any probability distribution, all values for P (g) are less than or equal to 1, histogram probability are mean, standard deviation, skew, energy and entropy.

1. **Mean:** the mean is the average value, so it tells us something about the general brightness of the image. A bright image will have a high mean, and a dark image will have a low mean. We will use L as the total number of gray levels available, so the gray levels range from 0 to L_1. For example, for typical 8-bit image data, L is 256 and ranges from 0 to 255. We can define the mean as follows:

$$g = \sum_{g=0}^{L-1} gP(g) = \sum_{r}\sum_{c} \frac{I(r,c)}{M}$$

If we use the second form of the equation, we sum over the rows and columns corresponding to the pixels in the image or sub image under consideration.

2. **Standard deviation:** Which is also known as the square root of the variance, tell us something about the contrast. It describe the spread in the data, so a high contrast image will have a high variance, and a low – contrast image will have a low variance. It is defined as follows:

$$\sigma = \sqrt{\sum_{g=0}^{L-1} (g - \bar{g})^2 P(g)}$$

3. Skew :the skew measure the asymmetry a bout the mean in the gray-level distribution .it is defined as:

$$Skew = \frac{\bar{g} - \text{mod}\, e}{\sigma_g}$$

This method of measuring skew is more computationally efficient, especially considering that, typically, the mean and standard deviation have already been calculated.

The energy measure tell us something a bout how the gray level are distributed

Energy = $\sum_{g=0}^{L-1} [P(g)]^2$

The energy measure has a maximum value of 1 for an image with a constant value and gets increasingly smaller as the pixel values are distributed a cross more gray level values(remember that al the P(g) values are less than or equal to 1).the lager this value is, the easier it is to compress the image data. If the energy is high, it tells us that the number of gray levels in the image is few, that is, the distribution is concentrated in only a small number of different gray levels.

4. **Entropy:** the entropy is a measure that tells us how many bits we need to code the image data and given by :

$$Entropy = -\sum_{g=0}^{L-1} P(g)\log_2[P(g)]$$

As the pixel values in the image are distributed among more gray levels, the entropy increases. This measure tends to vary inversely with the energy.