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# 2 Introduction

Image processing is one of the rapidly growing technologies of our time and it has become an integral part of the engineering and computer science disciplines. Among its many subsets, techniques such as median filter, contrast stretching, histogram equalization, negative image transformation, and power-law transformation are considered to be the most prominent. A histogram is a statistical representation of an image. It doesn't show any information about where the pixels are located in the image. Therefore, two different images can have equivalent histograms. For example, the two images below are different but have identical histograms because both are 50% white (grayscale value of 255) and 50% black (grayscale value of 0). We will focus on the histogram equalization.

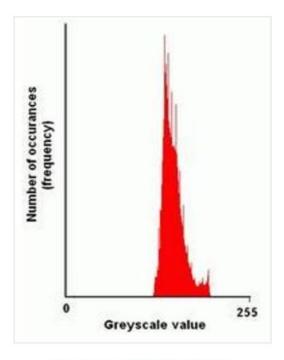


Image Source: Wikimedia Commons

## 3 THEORETICAL DEFINITIONS

#### 3.1 IMAGE

A digital image is a discrete space composed of small surface elements called pixel. Each one of this elements contains a value or a set of value coding the intensity level at each position. A digital image can be acquired with a great number of different devices such as a camera, an MRI machine or any kind of device with a sensor able to capture light intensity.[1]

Because of its discrete nature, the theory used to process digital image will rely on discrete domain, even if the analogy with the continuous domain is possible.

### 3.2 GRAY SCALE DIGITAL IMAGE

A grayscale (or gray level ) image is simply one in which the only colors are shades of gray. The reason for differentiating such images from any other sort of color image is that less information needs to be provided for each pixel. In fact a 'gray' color is one in which the red, green and blue components all have equal intensity in RGB space, and so it is only necessary to specify a single intensity value for each pixel, as opposed to the three intensities needed to specify each pixel in a full color image.

Often, the grayscale intensity is stored as an 8-bit integer giving 256 possible different shades of gray from black to white. If the levels are evenly spaced then the difference between successive gray levels is significantly better than the gray level resolving power of the human eye.[2]

Grayscale images are very common, in part because much of today's display and image capture hardware can only support 8-bit images. In addition, grayscale images are entirely sufficient for many tasks and so there is no need to use more complicated and harder-to-process color images.

#### 3.3 COLOR IMAGE

The human visual system can distinguish hundreds of thousands of different color shades and intensities, but only around 100 shades of grey. Therefore, in an image, a great deal of extra information may be contained in the color, and this extra information can then be used to simplify image analysis, object identification and extraction based on color.

The saturation is determined by the excitation purity, and depends on the amount of white light mixed with the hue. A pure hue is fully saturated, i.e. no white light mixed in. Hue and saturation together determine the chromaticity for a given color. Finally, the intensity is determined by the actual amount of light, with more light corresponding to more intense colors.[3]

# 4 HISTOGRAM

A histogram is a graphical representation that organizes a group of data points into user-specified ranges. Similar in appearance to a bar graph, the histogram condenses a data series into an easily interpreted visual by taking many data points and grouping them into logical ranges or bins.[4]

#### 4.1 Transformation of Histogram

#### 4.1.1 Normalization of a Histogram

Standardize a histogram is a method comprising into changing the discrete dispersion of powers into a discrete conveyance of probabilities. To do as such, we need to separate each worth of the histogram by

the quantity of pixel. Since a computerized picture is a discrete arrangement of qualities that could be viewed as a grid and it's identical to separate each nk by the element of the cluster which is the result of the width by the length of the picture.[5]

$$n_{kn} = \frac{n_{kn}}{\text{length} \times \text{width}} = pr(rk)$$

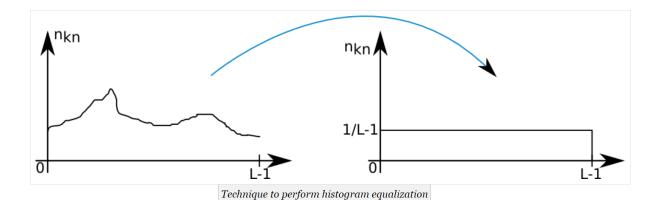
#### 4.1.2 Equalization of a Histogram

Histogram equalization is a method to process images in order to adjust the contrast of an image by modifying the intensity distribution of the histogram. The objective of this technique is to give a linear trend to the cumulative probability function associated to the image.

The processing of histogram equalization relies on the use of the cumulative probability function (cdf). The cdf is a cumulative sum of all the probabilities lying in its domain and defined by:

$$cdf(x) = \sum_{k=-\infty}^{x} p(k)$$

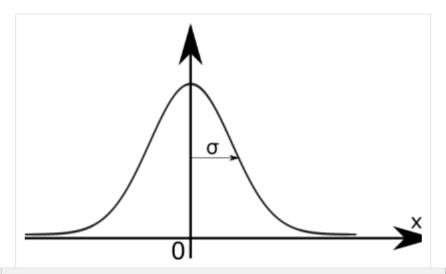
The idea of this processing is to give to the resulting image a linear cumulative distribution function. Indeed, a linear cdf is associated to the uniform histogram that we want the resulting image to have.



#### 4.1.3 Gaussian or Normal distribution

The Gaussian probability distribution function is a kind of pdf defined by:

$$\begin{cases} R \to [0,1] \\ G_1(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{\frac{-(x-m)^2}{2\sigma^2}} \end{cases}$$



Gaussian distribution with o mean and a standard deviation

# 5 Principle and realization of histogram equalization

Histogram Equalization is a method of enhancing image contrast. Its main idea is to change the histogram distribution of an image into an approximately uniform distribution, thereby enhancing the contrast of the image. Although histogram equalization is only a basic method in Digital Image Processing, it has a very powerful effect and is a very classic algorithm.

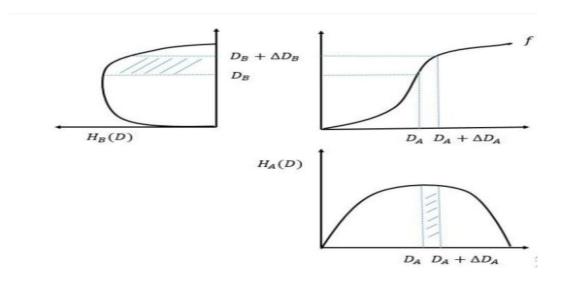
### 5.1 HISTOGRAM EQUALIZATION AND CONTRAST ENHANCEMENT

An example of image contrast enhancement is given below.the picture is a 338 \* 600 grayscale image. It can be seen that the car and the background are foggy and can't be seen clearly, the whole picture is dark, and the difference between the car and the background (ground, house) is not very obvious. Figure 2 is obtained after the histogram is drawn. It can be seen that most of the gray scales are

distributed between 100 and 180, and the histogram equalization needs to be done to make the histogram as evenly distributed as possible within 0 to 255.

#### 5.2 Principle and implementation of histogram equalization

Here is an introduction to the basic principles of Histogram Equalization. Suppose we now have an image A with histogram distribution . We want to use a monotonic nonlinear mapping, Change image A to image B, that is, apply to each pixel in image A Transform, the histogram distribution of image B is The whole process can be illustrated according to the diagram the lower right of the figure is the grayscale histogram distribution of image A (for drawing, here is a continuous distribution), the upper right of the figure is the monotonic nonlinear transformation function The histogram distribution of image B obtained in the upper left way, including The function is to change the grayscale of the pixels in the A image to All becomes. The above formula can be understood as the total number of pixels in the corresponding interval does not change. In order to achieve equalization of the histogram.



#### 5.3 Principle and implementation of adaptive histogram equalization

In the histogram equalization introduced above, the global image is directly equalized, which is Global Histogram Equalization, without considering the local image area (Local Region). The adaptive process is to use only the local area in the equalization process. The histogram distribution in the window to construct the mapping function.

The earliest paper on AHE comes from Image enhancement techniques for cockpit displays, First of all, the simplest and direct idea traverse each pixel of A image, use the W \* W window around the pixel to

calculate the CDF of the histogram transformation, and then Pixels are mapped. This is a very Naive method, and the computational complexity is outrageous. The following is a simple analysis. In the actual implementation process, according to the window size (W, W) and the affected area size (A, A), combined with the image size (M, N), the window can be moved by step A each time. Pay attention to the processing of boundary conditions. For example, when the window is located in the upper left corner of the image, the affected area is not (A, A), but the entire window. The same applies to the upper right, lower right, lower left and surrounding situations.

## 6 Practical Use

Histogram equalization is an important image processing operation in practice for the following reason. Consider two images f1f1 and f2f2 of the same object but taken under two different illumination conditions (say one image taken on a bright and sunny day and the other image taken on a cloudy day). The difference between these images can be approximated with an order preserving mapping  $\gamma\gamma$ ,  $f2=\gamma(f1)f2=\gamma(f1)$ .

It is not hard to prove that the histogram equalized versions of both images are equal:  $\Psi1f1=\Psi2f2$ . Here  $\Psi1$  and  $\Psi2$  are the histogram equalizing mappings defined above (these mappings are image dependent, that is why we write the subscript to denote the image).

Histogram equalization thus serves as a preprocessing step in vision systems to compensate for the effect of an unknown change in illumination (grey value scaling). For instance in a face recognition system where images of human faces have to be compared with other images of the same face (and most probably taken under different illumination conditions).[4]

# 7 How Histogram Equalization Works

The process for histogram equalization is as follows:

#### Step 1: Obtain the histogram.

For example, if the image is grayscale with 256 distinct intensity levels i (where i = 0 [black], 1, 2, .... 253, 254, 255 [white]), the probability that a pixel chosen at random will have an intensity level i is as follows.

#### Step 2: Obtain the cumulative distribution function CDF.

The cumulative distribution function H(j) is defined as the probability H of a randomly selected pixel taking one of the intensity values from 0 through j (inclusive).[6] Therefore, given our normalized histogram h(i) from above, we have the following formula:

$$CDF = H(j) = \sum_{i=0}^{j} h(i)$$
 where  $j = 0, 1, ...., 254, 255$ 

# Step 3: Calculate the transformation T to map the old intensity values to new intensity values.

Let K represent the total number of possible intensity values. j is the old intensity value, and T(j) is the new intensity value.

# Step 4: Given the new mappings of intensity values, we can use a lookup table to transform each pixel in the input image to a new intensity.

The result of this transformation is a new histogram which corresponds to a new output image.

#### **Special note on transformation functions:**

The formula we used for histogram equalization is a common one, but other transformation functions are possible. Different transformation functions will yield different output histograms.[6]

$$CDF = H(j) = \sum_{i=0}^{j} h(i)$$
 where  $j = 0, 1, ...., 254, 255$ 

# 8 THE CORE ALGORITHM

#### Step 1: Calculate normalized cumulative histogram

First, we calculate the normalized histogram of the image. Normalization is performed by dividing the frequency of each bin by the total number of pixels in the image. As a result, the maximum value of the cumulative histogram is 1. The following figure shows the normalized cumulative histogram of the same low contrast image presented[7]

#### Step 2: Derive intensity-mapping lookup table

Next, we derive a lookup table which maps the pixel intensities to achieve an equalized histogram characteristics. Recall that the equalized cumulative histogram is linearly increasing across the full range of intensity. For each discrete intensity level i, the mapped pixel value is calculated from the normalized cumulative histogram. As an intuition into how the mapping works, let's refer to the normalized cumulative histogram shown in the figure above. The minimum pixel intensity value of 125 is transformed to 0.0. The maximum pixel intensity value of 200 is transformed to 1.0. All the values in between are mapped accordingly between these two values. Once multiplied by the maximum possible intensity value (255), the resulting pixel intensities are now distributed across the full intensity range.

#### Step 3: Transform pixel intensity of the original image with the lookup table

Intensity of all pixels in the image are mapped to the new values. The result is an equalized image.

## 9 CODE IMPLEMENTATION IN MATLAB

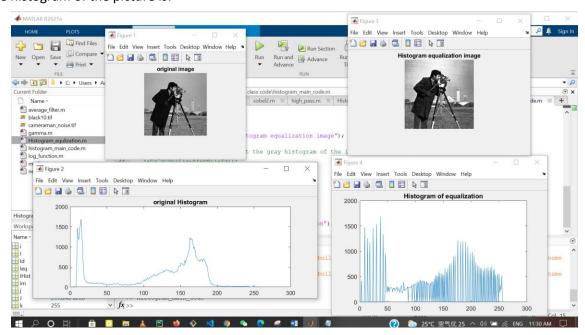
```
I=imread('cameraman.tif');
%read the image
imshow(I),title("original image");
%show the image
[M, N] = size(I); Id=double(I);
%convert the image in size and double
IHist=zeros(1,256);
for i=1:M
   for j=1:N
         IHist (Id(i,j)+1) = IHist(Id(i,j)+1)+1;
    end
end
figure, plot(IHist), title("original Histogram");
%Histogram normalization processing
IHist=IHist./(M*N);
Sk=zeros (1,256);
for k=0:255
 Sk(k+1) = sum(IHist(1:k+1));
% Requantization of gray levels
Smin=min(Sk);
Sk=uint8 (255*(Sk-Smin)./(1-Smin)+0.5);
%Output image equalized by histogram
Ieq=zeros(M,N);
for i=1:M
    for j=1:N
        L=double(I(i,j))+1;
        Ieq(i,j)=Sk(L);
    end
end
Ieq=uint8(Ieq);
figure, imshow (Ieq), title ("Histogram equalization image");
out=Iea;
%Traverse all pixels and count the gray histogram of the image after
equalization
%Ieq=double(gray2mat(Ieq));
IHist=zeros(1,256);
[M,N] = size(I);
for i=1:M
    for j=1:N
         IHist(Ieq(i,j)+1)=IHist(Ieq(i,j)+1)+1;
    end
end
figure, plot (IHist), title ("Histogram of equalization");
```

# **10 RESULTS**

Now look at the histogram equalization output for the two images presented in For each result, the upper two images show the original and equalized images. Improvement in contrast is clearly observed. The lower two images show the histogram and cumulative histogram, comparing original and equalized images. After histogram equalization, the pixel intensities are distributed across the whole intensity range. The cumulative histograms are increasing linearly as expected, while exhibiting staircase pattern. This is expected as the pixel intensities of the original image were stretched into a wider range. This creates gaps of bins with zero frequency between adjacent non-zero bins, appearing as flat line in the cumulative histogram.



#### The histogram of the picture is:



# 11 CONCLUSIONS

We looked at basic histogram equalization algorithm and implementation. As it is performed based on the histogram of the entire image, it is commonly referred to as global histogram equalization. It is a simple and effective tool to increase global contrast of images. However, if the image contains noises, these will be amplified as well. There are several algorithm variations to address this issue, such as adaptive histogram equalization (AHE) and contrast-limited adaptive histogram equalization. As you can clearly see from the images that the new image contrast has been enhanced and its histogram has also been equalized. There is also one important thing to be note here that during histogram equalization the overall shape of the histogram changes, where as in histogram stretching the overall shape of histogram remains same.

# 12 REFERENCE

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- [5] Kyaw Saw Htoon, "A Tutorial to Histogram Equalization | by Kyaw Saw Htoon | Medium," 2020. https://medium.com/@kyawsawhtoon/a-tutorial-to-histogram-equalization-497600f270e2 (accessed Jul. 23, 2021).
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